A Comprehensive Study on Tool Condition Monitoring Using Time-Frequency Transformation and Artificial Intelligence

Javad Soltani Rad

A Thesis

in

The Department

of

Mechanical and Industrial Engineering

Presented in Partial Fulfillment of the Requirements

for the Degree of Master of Applied Science at

Concordia University

Montréal, Québec, Canada

April 2015

CONCORDIA UNIVERSITY

School of Graduate Studies

This is to certify that the thesis proposal prepared

By: **Javad Soltani Rad**

Entitled: **A Comprehensive Study on Tool Condition Monitoring Using Time-Frequency Transformation and Artificial Intelligence**

and submitted in partial fulfilment of the requirements for the degree of

Master of Applied Science

complies with the regulations of this University and meets the accepted standards with respect to originality and quality.

Signed by the final examining committee:

____________________ Dr. G. Gouw, Chair

____________________ Dr. Y. Zeng, Examiner, External

____________________ Dr. R. Sedaghati, Examiner

____________________ Dr. Y. Zhang, Supervisor

____________________ Dr. C. Chen, Supervisor

Approved by ____________________________

Dr. Martin D. Pugh, Chair

Department of Mechanical and Industrial Engineering

____

Dr. Amir Asif

Dean, Faculty of Engineering and Computer Science

ABSTRACT

A Comprehensive Study on Tool Condition Monitoring Using Time-Frequency Transformation and Artificial Intelligence

Javad Soltani Rad

Tool failure is one of the probable faults during machining process which may cause unscheduled downtime and damage of tools, machines and work pieces. Therefore, developing an accurate and reliable online tool condition monitoring (TCM) system is in high demand. This research investigates TCM using time-frequency transformation methods and artificial intelligence. Multi-sensory monitoring systems and sensor fusion are investigated in the first step. Many different sensors at various locations are tested to determine the best input sets with most complimentary information. Three data fusion techniques 1) feature level, 2) score level, and 3) decision level are implemented and compared in this step. The result suggests that score level data fusion is superior for this application. Moreover, five advanced time-frequency transformation methods are employed due to superior ability of time-frequency transformation to reveal time variant characteristics of a signal as well as its frequency components. S-transform demonstrates the most accurate results among these methods. This research also proposes a novel feature extraction method to select the most discriminative information and reduce data's dimensionality and calculation cost. This method selects a local region of data in time-frequency domain using genetic algorithm optimization. The proposed method is also combined with 2D principal component analysis which has improved the systems in terms of accuracy and performance. Finally, three well-known artificial intelligence methods 1) multi-layer perceptron artificial neural network, 2) radial basis function artificial neural network and 3) adaptive neuro-fuzzy inference system are applied to find a model between extracted features and system fault. Based on the results, radial basis function has the minimum mean error and adaptive neuro-fuzzy produces the lowest maximum error.

Dedicated to

Fatemeh, my lovely wife

for her constant love, support and patience

and being with me all the way

and my most wonderful family

for their unending love and support.

ACKNOWLEDGEMENTS

I would like to express my deepest appreciation to my supervisors, Professor Youmin Zhang and Professor Chevy Chen for giving me intellectual freedom in my work, engaging me in new ideas, supporting my thesis by their vast knowledge and skills and demanding a high quality of work in all my endeavors.

I would like to thank all my friends and colleagues who helped me get through the difficult times. I am especially grateful to Dr. Saman Bashbaghi for his support and guidance in my research and life. My special thanks to my friends Ensieh, Mohammad, Iman, Hamed, and all those people who have given me support and I did not have the chance to thank them.

Lastly, and most importantly, I would like to thank my sweet wife and best friend, Fatemeh, who has been my inspiration and motivation by standing beside me throughout this work. I would also like to thank my family for their continued support and encouragement through my entire life. Without such a team behind me and their love I would not have finished this thesis.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

NOMENCLATURE

Abbreviations and Acronyms

TCM	Tool Condition Monitoring
PLS	Partial Least Square
SRC	Selective Regional Correlation
TF	Time-Frequency
AI	Artificial Intelligence
AE	Acoustic Emission
Vib	Vibration
AC	Alternating Current
Vb	Tool Flank Wear
PCA	Principal Component Analysis
ANN	Artificial Neural Network
BN	Baysian Network
ANFIS	Adaptive Neuro-Fuzzy Interference System
LP filtering	Low Pass Filtering
HP filtering	High Pass Filtering
RMS	Root Mean Square
STFT	Short Time Fourier Transform
WT	Wavelet Transform
ST	S-Transform
PW	Smoothed Pseudo-Wigner-Ville Distribution
CW	Choi-Williams Distribution

Abbreviations and Acronyms

MLP	Multi-Layer Perceptron
BEP	Back Error Propagation
RBF	Radial Basis Function
FIS	Fuzzy Interference System
NRMSD	Normlized Root Mean Square Deviation

Chapter 1

Introduction

Conventional machining operations, which include turning, milling, and drilling, are among the most common activities in the manufacturing industry[1]. Turning refers to removing the unwanted material while the part is rotated and a cutter with single cutting edge moves along the workpiece to cut[2](Figure1.1). Milling is a process of using multi-toothed rotating cutters to remove material from the surface (face milling) or periphery (end milling) of the workpiece[3,4](Figure1.2). Drilling is also a cutting process which uses a rotary drill bit advanced along its rotation access to make or enlarge a hole in the workpiece material[5](Figure1.3).

The increasing demand for higher product rate, quality, reliability, and manufacturing efficiency has imposed strong desire for total autonomy in manufacturing industry[3,6]. In a machining center, the cutting tool gradually wears out due to thermal fracturing, attrition, abrasion, plastic deformation, diffusion, chemical wear, and grain-pullout, etc.[7]. This affects the machining process, health of the machine tool, the product quality and may cause unwanted vibration, spoils the surface finish and causes dimensional inaccuracy[7]. The cutting tool may also break while it is engaged with the workpiece. Cutting tool breakage can cause unscheduled downtime which is costly, not only in terms of time lost, but also in terms of tools, machines and work pieces damaged or destroyed. Some researchers estimated that the amount of downtime due to tool breakage is about 20% of the total machine downtime[1,8].

Moreover, to reduce manufacturing costs, ideally, cutting tools should be maximally utilized as tooling is quite expensive. On the other hand, estimation of the tool wear can help to decide about possible optimization of the machining parameters (cutting speed, feed rate and depth of cut). Estimation of tool wear is also helpful for tool wear compensation. It can also increase production quality and efficiency. Therefore, it is in high demand for manufacturing industries to continuously monitor the tool wear condition during the machining process[7].

Figure 1.1: Turning operation[9]

Among many possible tool faults, there are three most common cases in the industrial applications.

1- Tool wear which can directly influence the size and quality of the finished surface and also cause fatigue endurance limit changes. It can also influence lubrication retention capability by changing the distribution of heights and slopes of the surface. Furthermore, excessive tool wear can lead to tool breakage.

2- Tool breakage and fracture which is the dominant mode of failure for more than one quarter of all advanced tooling material.

3- Chatter (the self-excited vibration of the machine tool that causes the instability of the cutting process) which is often a serious limitation to achieving higher rates of removal. Moreover, it deteriorates the surface finish, affects dimensional accuracy, and may cause tool and machine damaged.

Therefore, a tool fault detection system is crucial to detect the faults rapidly and make a proper action before it damages the workpiece, tool, or the machine. Additionally, it should be accurate to eliminate unnecessary downtime due to false alarms[10].

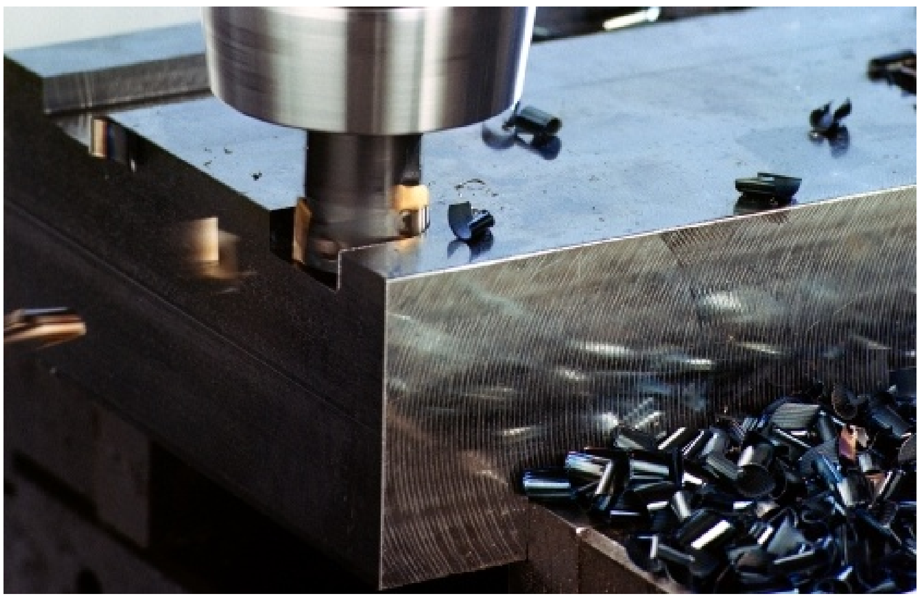

Figure 1.2: End milling operation[11]

A process monitoring system generally performs its task through the analysis of process measurements such as force, vibration, power, acoustic emission , etc. Any deviation from normal situation is considered as an abnormality in the system and the source of this change should be determined for further analysis[10]. This research investigates tool wear monitoring in milling operation due to its importance in the todays industry. The goal is to develop an online reliable method for tool condition monitoring purposes. Tool wear is considered as the monitoring variable due to its frequency in machining operation. The developed method should be practical and inexpensive to be used in the industry. It needs to be capable of online use and able to produce immediate responses. It should also have a high accuracy and fault detection/estimation performance.

Figure 1.3: Drilling operation[12]

1.1 Tool Condition Monitoring (TCM)

A general methodology for developing an intelligent monitoring system for machining is composed of four key components[13]:

1- Sensors: Sensor refers to a device which transforms a physical quantity into the corresponding electrical signals. Selecting the best sensor and process variable is an important step in TCM. The ideal variable for monitoring purposes is the one that is highly sensitive to the parameters we want to monitor, however, it is insensitive to the other process parameters[10]. Reliability, applicability in industrial environment and cost of the sensors are also among the other factors should be considered[13,14].

2- Signal processing: A suitable signal processing strategy is compulsory in this step because of the high levels of mechanical, electrical and acoustic noises in industrial environments. Moreover, Signal processing helps to determine whether the change in the signal is due to tool wear or a change in the process conditions. Signal processing can be more or less complex due to the nature of signals and the strategy to solve the problem[13,14].

3- Feature generation, selection/extraction: The signal acquired by sensors has to be transformed into appropriate features which represent the desired characteristics of the system. Many features can be extracted from a signal which are well correlated with the desired monitoring fault from time, frequency and time–frequency domain. Afterwards, it should be decided that which of the generated features are the best system reflectors. Feature selection and feature extraction are two useful methods to define the most useful sensory features[13,14].

4- Artificial Intelligence (AI) or mathematical models for decision making: The monitoring system should be able to learn complex non-linear relationships between faults and relevant extracted features from signals. Previous knowledge of the process, the nature of the process and model, number of experimental samples and the desired model accuracy are among the points should be considered in the selection of AI algorithm. Finally a decision should be made based on the output of AI. Instead of AI methods, mathematical models can be used as well[10,13,14]. Figure1.4 presents the steps of TCM.

Figure 1.4: Steps to design a tool condition monitoring system

1.1.1 Sensors

The first step of process monitoring is to select and make appropriate use of some sensors which provide the most discriminative information of the machining process. Dynamometers, accelerometers, acoustic emission sensors, current sensors, ultrasonic sensors, temperature sensors and optical sensors are explained in this section as the most common sensors used in this application.

- Dynamometers

Dynamometers are sensors to measure cutting force. Cutting force is a variable that best describes the cutting process and can reflect different features of cutting. It is very sensible to faults during machining specially tool faults and can reflect it accurately[13]. Cutting force signals have been widely used for monitoring purposes in all machining processes (turning, milling, drilling, etc.)[1]. This signal can reflect surface quality and properties and may be applied for wear, breakage and chatter detection[13].

One of the drawbacks of using dynamometers is that any change in cutting force due to a fault is strongly dependent on other cutting conditions together with the cutting material, work material, etc. Furthermore, it is very difficult to apply them in industry mainly because of the high cost of multi-axis dynamometers, their intrusive nature in production environments and the limited frequency response they can provide[13].

- Accelerometers

Accelerometers are sensors to measure vibration. Vibration is another significant factor which is able to reflect tool conditions, surface roughness, and dimensional accuracy in machining processes[15]. Vibration monitoring is common for prediction of surface roughness especially in turning process. Vibration amplitude usually varies during machining due to the progressive flank wear which provides a tool signature. Vibration signals can also be used for tool breakage detection as the cutting vibration alters due to tool breakage[13,14].

Monitoring systems based on accelerometers are practical and cost-effective and have the advantage of simplicity. However, vibration signals may not be as accurate and reliable as dynamometer or acoustic emission signals. Vibration is highly sensitive to machining speed. It should remain within a specific range during the monitoring which is one of the accelerometer drawbacks[13,14].

- Acoustic Emission (AE) Sensors

As a material (tool, workpiece, machine body, etc.) undergoes stress, a transient elastic energy is released from it which is called AE. This stress may be generated by deformation, fracture, friction and thermal reactions of the tool, chips, workpiece, machine body and etc. The frequency range of AE signals is much higher than the frequency range of the machine vibrations and environmental noises which is its advantage for monitoring purposes, however, it is really sensitive to cutting parameters which makes the signal processing and feature extraction very important.

A large amount of AE is generated during tool breakage and fracture which makes AE signal to be well suited to the tool breakage detection. However, there is still a debate in the literature about the usage of AE in detection of other faults such as wear. AE sensors are easy to install and inexpensive, but they are sensitive to location. Therefore, they should be located in an appropriate position and carefully calibrated[13,14].

- Current and Power Sensors

Motor armature current is proportional to cutting forces, therefore, current measurement is an indirect way to sense the machining forces. Power sensors measure the spindle or axis drive power and their application and limitations are basically similar to current sensors. These sensors are not as accurate as dynamometers, however, they are low cost and easy to install which makes them a suitable candidate to be used as complementary information in monitoring systems. One of the major defects of these signals is that they do not cover high frequency components of cutting forces. Therefore, they are not appropriate for applications which need immediate response[13,14].

- Other Sensors

Temperature sensors, optical sensors and ultrasonic sensors are among other sensors can be used for monitoring purposes. Temperature of the cutting zone reflects cutting process very well. For example, it varies with the tool wear because of the changes in the tool geometry and its ability to cut, however, it is very difficult to measure accurate cutting temperature. As a result, average temperatures around the cutting tool is usually used instead of the exact value which may cause loss of information[13].

Ultrasonic sensors and optical sensors also have been applied to monitor the surface quality, roughness and etc. An ultrasonic pulse is sent by an ultrasonic sensor to the surface and the amplitude of the returned signal is used to build a model. Optical sensors work based on the intensity of the beam of the light that is reflected from the machined surface in the specular direction and it can be correlated with the surface quality[13].

- Sensor Fusion Concept

If cutting parameters change, the sensitivity and the noise rejection of the sensed signal changes and this can affect the reliability of the monitoring system significantly. Using more than one sensor is useful in this situation to avoid uncertainty. It should be considered that some sensors may represent the same information. For example, a dynamometer and a current sensor provides the same information with different level of accuracy. Therefore, using them together is not considered as sensor fusion. In sensor fusion, sensors should be selected in a way to represent complementary information. Using AE and vibration or force signals are good examples of sensor fusion as they are less correlated and can be used effectively[13,14]. Another approach is using multiple sensors from the same type to mainly improve the reliability.

1.1.2 Signal Processing

There are high levels of mechanical, electrical and acoustic noises in industrial environments. Moreover, indicator signals may change due to changing the process as well as fault occurrence. Therefore, a signal processing operation is mandatory before feature generation/selection step.

After data acquisition by sensors, signal is filtered to keep the signal within the range of the frequency response of the sensor and to avoid noises. The next step is to convert a continuous signal to a discrete signal called sampling. After this step the analog signals will be changed to digital signals.

Digital filtering is next possible step which involves some quality improvement methods and noise reductions. The main function of digital filtering is to keep the principal components of a signal which have most correlation with the variable we are monitoring. For example, cutting force signal may be filtered so as to be able to study only the signals' information which is closely related to the cutting tool wear and cutting mechanism such as the signals' information at the tooth-pass frequency. Furthermore, transient mechanical events like breaking of a built-up edge, local variation in hardness over the work piece, etc. may cause high frequency noises and signal oscillations which can be prevented by digital filtering.

Many different operations and methods can be used for finding the most informative portion of a signal with respect to the fault and signal enhancements in time domain, frequency domain, time-frequency domain and etc. Signal segmentation is another optional operation which can be performed to extract the signal information when the cutting tool is actually removing metal in a steady state[13,14].

Finally, the signal is ready to be used in the feature generation, selection and extraction step.

1.1.3 Feature Generation, Selection/Extraction

The next step is feature generation and selection. The features which are most related to what we are monitoring should be generated and selected at this step. The nature of the signal is very important in deciding which feature better represents the signal. Many different features of a signal can be extracted in time domain, frequency domain and time-frequency domain. In the feature generation step, a large number of features may be generated. Therefore, it should be decided that which set of features are more appropriate for our application.

It is difficult to manually estimate which features are more sensitive to fault due to various factors such as machine tool characteristics, material properties, lubrication, location of the sensors, signal to noise ratios of the data acquisition system, etc. that can influence the effectiveness of the features. Therefore, a systematic approach to reduce the number of features for the successful development of reliable and robust TCM system is helpful[13,14].

Dimensionality reduction is useful as it can lead to less complicated learning algorithms and simpler robust models on small datasets with less variance. However, it should be noted that feature reduction should not affect the accuracy of the prediction and principal features of the signal should not be neglected during this procedure[13].

Two methods can be used for dimensionality reduction of feature space. Feature selection methods which refer to selecting a number of features by feature ranking based on their correlation with the monitoring variable. Subset selection is an example of this approach benefits from optimization algorithms such as genetic algorithm which helps in the optimal subset selection. After selecting the most discriminative features, non-selected features no longer be employed. Therefore it helps to reduce computational cost.

The second approach is called feature extraction which refers to finding a new set of k features that are a combination of the original d features. This approach has a higher degree of freedom in finding the set of the most significant features in comparison to the feature selection. Principal component analysis (PCA) is the main feature extraction technique which has a great potential in making principal features based on the sensor features[13,14].

Increasing number of features generally leads to a lower training error, however, not necessarily a lower validation and test error. Dimensionality reduction methods may improve the reliability of the monitoring system, however, the new features do not provide a physical explanation of the system[13,14].

1.1.4 AI Techniques for Decision Making

Indirect monitoring involves determining a system state based on physical signals which indirectly reflect the system and fault's information. Therefore, a more complex and accurate model is necessary in monitoring these systems to interpret information from sensors, eliminate unnecessary information, identify abnormalities and make an appropriate decision. Artificial intelligence (AI) is a good solution to build such a model. Artificial neural networks (ANN) are the main AI techniques applied for modeling and monitoring machining systems. Fuzzy logic systems and hybridization of them with ANN, called neuro-fuzzy inference systems, are also among the techniques having been widely used. Other AI approaches such as Bayesian network hidden Markov models or support vector machines are also applicable but not used as widely as the mentioned methods[13]. Figure 1.5 presents the frequency of usage of AI approaches in machining applications.

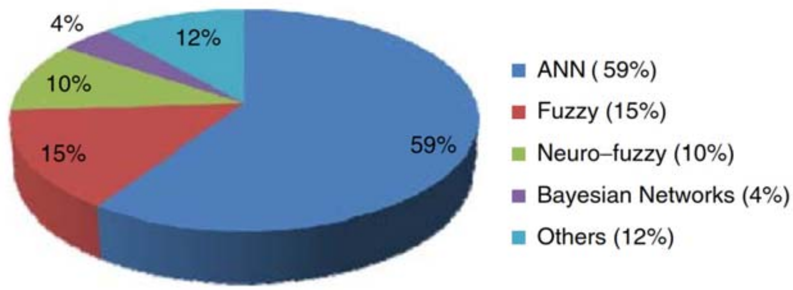

Figure 1.5: Frequency of usage of AI approaches in intelligent machining systems in the research platform ISI-Web of knowledge[13].

Many factors can influence choosing an AI technique such as monitoring purpose, experimental dataset for modeling the process, training and development duration, previous knowledge of the process etc. Advantages and disadvantages of a number of the most used techniques in this application is provided as follows:

- ANN

This method has the potential to provide high accuracy even in the cases that there is no previous knowledge of the process. The most important disadvantage of these systems is that they need a large number of training data. They are also not suitable to be used in the applications which require the inverse problem solving, such as the selection of cutting parameters to ensure a certain value of machining performance[13,14].

- Fuzzy Inference Systems

One of the applications of these systems is when the experimental data set consists of low/medium number of samples. In these systems, part of the model is developed using previous knowledge in a qualitative way. Therefore, this approach is used where there is enough knowledge from the process and this knowledge is intended to help the model to be more accurate. One of the other applications is where the inverse problem has to be solved. However, the accuracy of these systems are generally less than ANN[13,14].

- Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

Neuro-fuzzy systems are a hybridization of ANN and fuzzy systems to benefit from the advantages of both. Therefore, their application is a combination of both ANN and fuzzy systems. They are used when previous knowledge needed to be added to system and hidden knowledge from experimental data should be extracted[13,14].

- Bayesian Networks (BN)

Bayesian networks have generally less accuracy but more reliability in comparison to the other methods. The aim of these systems is to extract hidden knowledge from experimental data in the form of causal relationships and probabilities as well as using previous knowledge. They comparatively, need large training data and can be used for solving inverse problems such as finding the optimal cutting parameters[13,14].

1.2 Literature Review

This section presents the previous researches on machining monitoring and provides some potential research topics in this field. Two different methods are implemented in the literature and practice for monitoring the machining process in order to predict part accuracy and diagnose cutting-tool state: direct and indirect methods. Direct methods refer to a direct measurement of the tool condition using sensors like laser, optical, and ultrasonic sensors. The drawbacks of these methods are that they are still very expensive, not suitable for online application and also difficult to apply in the machining process environment. On the other hand, indirect methods monitoring systems are more economical. These systems infer the machining state by relating it to the physical parameters of system such as cutting forces, vibrations, temperatures, current consumption, etc.[13,14].

There exist a large number of tool condition monitoring methods in the literature which use different sensors for indirect tool condition monitoring. Four sensors have been widely applied to monitor machining systems: dynamometers, accelerometers, acoustic emission (AE) sensors and current sensors[13,16].

Cutting force is the variable that can describe the cutting process perfectly and many researches employed this feature for tool condition monitoring[17–22]. In their study, Liu et al.[23]have designed an online tool wear monitoring system based on cutting forces in turning of stainless steel parts. They employed back-propagation neural networks (BPNs) and the adaptive neuro-fuzzy inference system (ANFIS) for classification of the tool condition. While cutting forces have been proven to be sensitive to tool faults, the change in cutting force due to tool wear is strongly dependent on other cutting conditions together with the type of wear, cutting material, work material, etc. Moreover, dynamometer are relatively expensive to industrial usage[13].

It is also common to use vibration and AE signals as fault indicators in monitoring algorithms based on their ease of use in industry[15,24–31]. Vibration amplitude usually varies as a result of tool fault in machining process which makes vibration monitoring also an effective way for tool condition monitoring. As an example, vibration signal is employed in deep hole boring operation for tool condition monitoring[32].

AE signal derived from metal cutting also can represent the tool condition as it consists of continuous and transient signals, which have distinctly different characteristics in faulty situations. An important advantage of using AE signal is that its frequency range is much higher than that of machine vibrations and environmental noise, however, it is sensitive to sensor location and cutting parameters[13]. Kosaraju et al.[33]proposed an AE-based tool condition monitoring method in turning titanium with PVD-coated carbide tools. Power signal is also a practical and inexpensive cutting condition indicator in the industrial environment[34,35]. For instance, a tool condition monitoring system is designed based on the power signal of spindle and S-transform[36].

Any change in cutting conditions such as machining parameters, tool wear, machine stiffness, etc. may manipulate the sensitivity and the noise rejection of the sensed signals. Using several sensors is a strategy to increase the reliability of sensor's information under varying conditions and also it helps to avoid uncertainty [13]. Implementing multiple sensors with non-complementary measurements defines a multi-sensor monitoring system while sensor fusion refers to the use of more than one sensor signal in a complementary manner to provide a more robust monitoring system[13].

Ghosh et al.[7]have developed a neural network based sensor fusion method for tool wear monitoring in milling operation. Some features from cutting forces, spindle vibration, spindle current, and sound pressure level signals have been extracted and combined to estimate the flank wear of the tool. In another study, force, vibration and acoustic emission signals are used for tool condition monitoring based on a fuzzy inference system[37]. Wang et al.[38]has combined a direct sensor (vision) information with an indirect sensor (force) for online tool condition monitoring in milling operation. Cho et al.[39]have designed a multi-sensor fusion-based tool condition monitoring system in end milling. The sensors employed in the study were force, vibration, acoustic emission, and spindle power sensors and features from time domain and frequency domain were extracted. Based on the literature review, there is not still a strong conclusion which set of signals provide best results in sensor fusion. Moreover, different data fusion techniques are not studied in depth in this application.

After signal acquisition, a set of features with best correlation to tool fault condition should be extracted from the acquired signals. The features are desired not to be affected by process conditions[14]. The features can be extracted from time domain, frequency domain, statistical domain and time-frequency domain. Time domain descriptors simplicity in terms of extraction makes them easy to use, however, they are susceptible to disturbances[13,14]. Frequency and statistical domain feature extraction is also popular among researchers[14]. While these techniques provide acceptable performance in stationary conditions, they fail to provide robust result in non-stationary situations which could result from fast operational condition or the presence of a fault causing a discontinuity in the signal[40].

Due to non-stationary nature of faulty signals, time-frequency domain representation can reveal rich information about machinery health conditions by identifying the signal frequency components and revealing their time-varying features at the same time. Therefore, discriminative fault features can be extracted from a faulty signal by choosing a proper time-frequency transformation method[41]. However, there is still a lack of using advanced time-frequency methods for signal processing in the field of machining monitoring[16]. While many advanced time-frequency transformation methods have been tested with promising result in similar applications, there is not a comprehensive comparative study to report the efficiency and performance of these methods in tool condition monitoring.

In order to make the fault detection problem solvable, time-frequency domain information of a signal should be converted to feature vectors ideally containing only relevant information. Linear transformation methods such as principal component analysis and partial least squares (PLS) can be utilized to decrease the time-frequency information dimensions and construct a feature vector. However, for high dimensional datasets, computing the features increase the calculation cost and the obtained components are not always representative of the most discriminative information. Selecting a local confined portion of data instead of the entire time-frequency plane can help to conquer this problem. However, in local-based analysis, the important issue is the selection of the size and location of relevant area which is highly dependent on the final application[42]. Selective regional correlation (SRC) is a local time-frequency analysis method which is used by Rehorn et al.[3]for detection and diagnosis of brush seizing faults in the spindle positioning. However, to the authors' best knowledge, an effective local time–frequency feature generation method with the ability of finding the most relevant information still has not been addressed in the field of TCM.

Monitoring systems require reliable models for making a decision based on the extracted feature. The models should be capable of learning complex non-linear relationships between process operation variables, extracted features and the system's faults[13]. Artificial intelligence methods are good candidates to perform this task. Based on the literature, artificial neural network, fuzzy logic and neuro-fuzzy systems are leading methods for this application[13,14,16,43–50]. Bayesian networks, hidden Markov models, evolutionary algorithms and support vector machines are also gaining more attention recently[13,14,51–53]. An appropriate artificial intelligence method should be selected according to the monitoring purpose, the experimental dataset and number of extracted features for modeling the process, the previous knowledge of the process and training time as the final step for decision-making.

Based on the literature review, there is a high potential in literature to study sensor selection, multi-sensory systems, and sensor fusion concept. Moreover, the effects of locations of the sensors and different levels of data fusion on the monitoring algorithms are still not addressed in the literature. Time-frequency signal processing methods deserve more attention due to their superior ability to interpret time variant signals. An efficient method for dimensionality reduction is also necessary to make time-frequency interpretation more practical. Finally, the applicability and performance of artificial intelligence methods need to be investigated in combination with the signal processing and feature generation techniques.

1.3 Thesis Outline

The thesis is organized as follows: Chapter1provides an introduction to the concept of tool condition monitoring, explains the monitoring steps, reviews the recent literature, and describes the potential subjects of research in this field. Chapter2presents the methodology and mainframe of monitoring systems in this research and introduces the experimental dataset for validation of this research. Chapter3to6each represents one of the steps of tool condition monitoring. Chapter3deals with sensor fusion concept, multi-sensor systems and different methods of data fusion. Chapter4 is devoted to a comparative study between popular time-frequency transformation methods as powerful signal processing tools and compares the performance of five superior techniques. Chapter5presents a novel feature selection method proposed in this study to reduce the dimensionality of time-frequency transformation output and make the problem solvable. Chapter6compares three well-known artificial intelligence methods employed for making a model between extracted features and tool wear state. Finally, Chapter7draws the conclusion and outlines the future extensions of this study.

Chapter 2

Methodology Overview

This chapter consists of two sections. In the first section the methodology of tool condition monitoring employed in this research is explained and the techniques and approaches in each step are defined. The next section deals with experimental dataset which is used for validation of this work. Available monitoring signals and characteristics of the benchmark dataset are explained and clarified.

2.1 The Monitoring Algorithm Framework

In this section the methodology of designing an automated tool condition monitoring system for this research is explained. The intelligent monitoring systems comprised of four main components. The first step in tool condition monitoring is signal acquisition. These signals play the role of fault indicator in our system. After signal acquisition, the signals should be processed to improve their quality. Depending on the needs and characteristics of the signals, signal processing may include amplification, low pass and high pass filtering, time domain, frequency domain, or time-frequency domain processing etc.

After processing the signal, appropriate features should be extracted from that.

An ideal feature is the one which reflects our system monitoring variable characteristics perfectly and it is invariant with respect to other process parameters. Finally a machine learning algorithm should identify the relations between extracted features and corresponding system state. Based on the information that monitoring system provides from the machining process and machine state, appropriate commands should be sent to the machine for possible adjustments, or in extreme cases, stopping the process.

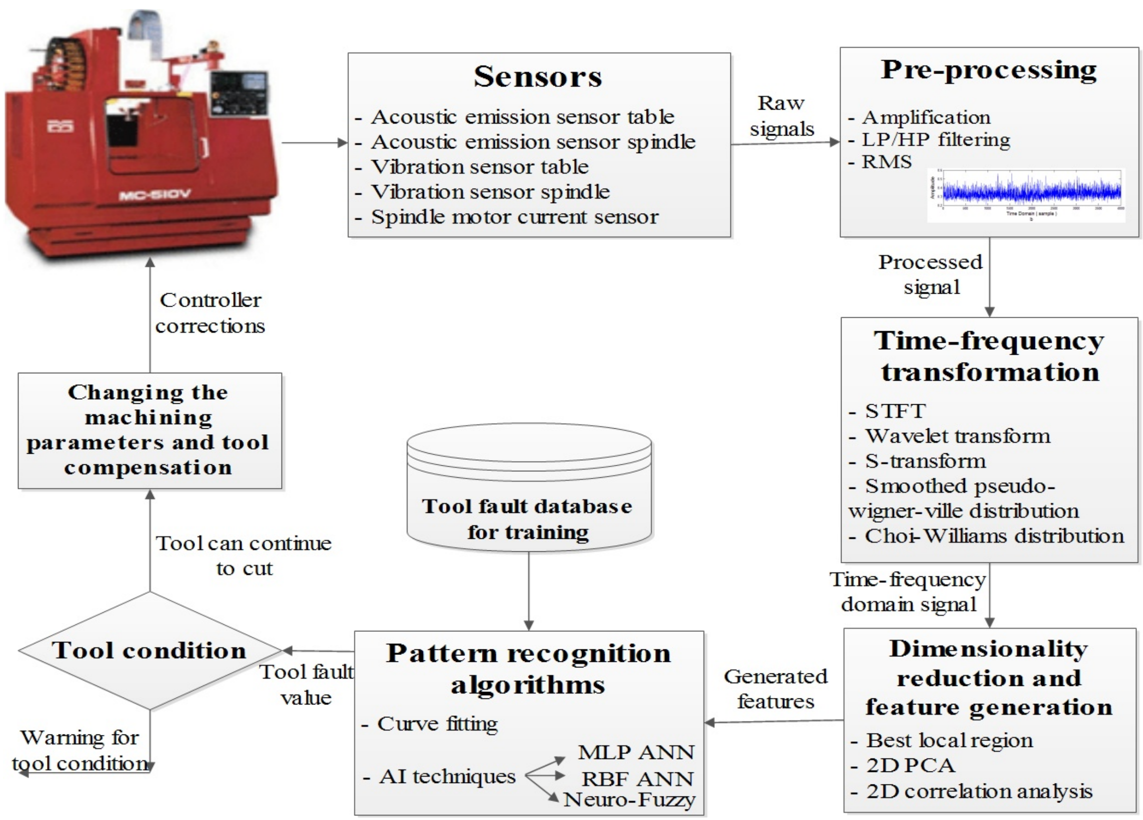

Figure 2.1: The general framework of the tool condition monitoring systems in this research

Figure2.1represents the baseline of the monitoring system in this work. In this research, two AE sensors and two vibration sensors are utilized. One of sensors is mounted on the machine table and the other on the spindle of machining center to collect information from the machine. A current sensor also provides necessary information of the current of the spindle motors. Chapter3discusses possible fusion techniques of these signals and provides a comparative study on which pair of signals has best accuracy. Due to the environmental noise and to improve the signal quality, some pre-processing operations are performed to each signal. These pre-processing operations for each individual signal are explained in the following section.

The next step is to process signal to prepare it for feature extraction. Five advanced signal processing methods are employed in this step and the results are compared in Chapter4. Feature extraction is the next necessary step to make the monitoring problem solvable.

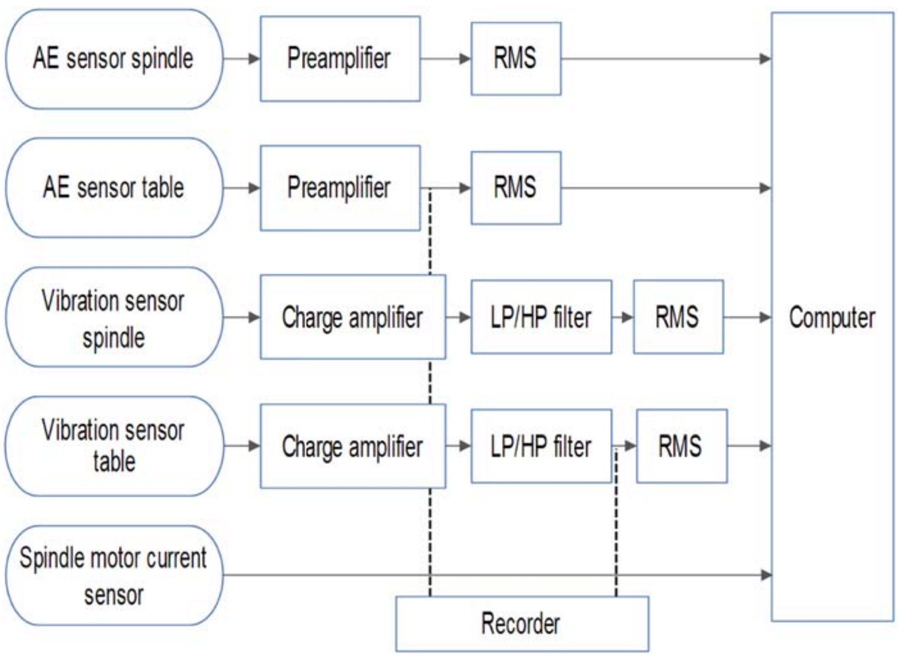

Figure 2.2: Schematic diagram of the the experimental setup[54]

The results of time-frequency transformation have high dimensions and a method should be utilized to convert them to the most informative features which can represent the important characteristics of the system comprehensively and also have less dimensions to be applicable for online use. A novel method to find the best local region of time-frequency domain is proposed and it is combined with 2D principal component analysis (2D PCA) in Chapter5. In this step, the results of using the

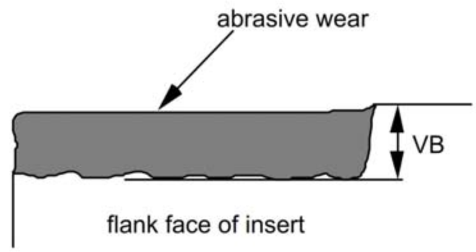

Figure 2.3: Tool wear as it seen on the insert[54]

whole information of time-frequency domain, using the best local region approach and using the combination of best local region and 2D PCA are implemented and compared.

After preparing the informative low dimensional features, an artificial intelligence method is necessary to find a model between the extracted features and system state. The method should have the ability to deal with complex non-linear situations. For this purpose, three most popular artificial intelligence methods in mechanical condition monitoring are employed in Chapter6and the performance results are compared. Real experimental data is utilized for training the system and the trained system can be used online to estimate the tool fault severity. Based on the estimated tool fault, a threshold can decide whether the system should continue to cut or the cutting should be stopped. The tool fault value can be exploited to optimize the machining parameters and tool compensation.

2.2 Experimental Dataset

The NASA Ames and UC Berkeley benchmark milling dataset[54]is used for methodology validation. This dataset consists of experiments from runs on a milling machine under various operating conditions. The Matsuura MC-510V machining center is used for experiments. The advantage of the dataset for this research is that it provides diverse signals information acquired from various practical commonly used sensors for tool condition monitoring. In this dataset, depth of cut, feed rate and workpiece material as the operation variables are subjected to change and the tool wear was investigated in a regular cut as well as entry cut and exit cut. The experiment setup is depicted in Figure2.2.

Two acoustic emission sensors (model WD 925) and two vibration sensors (model 7201- 50, ENDEVCO), are each mounted to the table and the spindle of the machining center and a current sensor (model CTA 213) of spindle is used for signal acquisition. All sensors' signals except current sensor are amplified and filtered and fed through two root mean square (RMS) filter. Figures2.4to2.8present samples of each dataset signal. A 70mm face mill with 6 KC710 inserts was chosen based on its industrial applicability as the cutting tool.

Tool flank wear (Vb) as a generally accepted parameter for evaluating tool wear is investigated as the monitoring variable. Flank wear refers to the distance from the cutting edge to the end of the abrasive wear on the flank face. Figure2.3 presents an image of tool wear as it is seen on the insert. After each experimental run, the insert was taken out of the tool and the flank wear was measured with the help of a microscope.

The data is organized in a MATLAB structure array. Table2.1provides a description of the structure fields. There are 16 cases each includes varying number of runs depending on the degree of measured flank wear up to a wear limit (and sometimes beyond). In each case, operation conditions are constant and workpiece material is cast iron or steel. Table2.2represents the operation condition of 16 cases in the dataset.

Table 2.1: Names and descriptions of dataset structure elements in MATLAB

Field Name	Description
case	Case number (1-16)
run	Counter for experimental runs in each case
VB	Flank wear, measured after runs
time	Duration of experiment (restarts for each case)
DOC	Depth of cut (does not vary for each case)
feed	Feed (does not vary for each case)
material	Material (does not vary for each case)
smcAC	AC spindle motor current
smcDC	DC spindle motor current
vib_table	Table vibration
vib_spindle	Spindle vibration
AE_table	Acoustic emission at table
AE_spindle	Acoustic emission at spindle

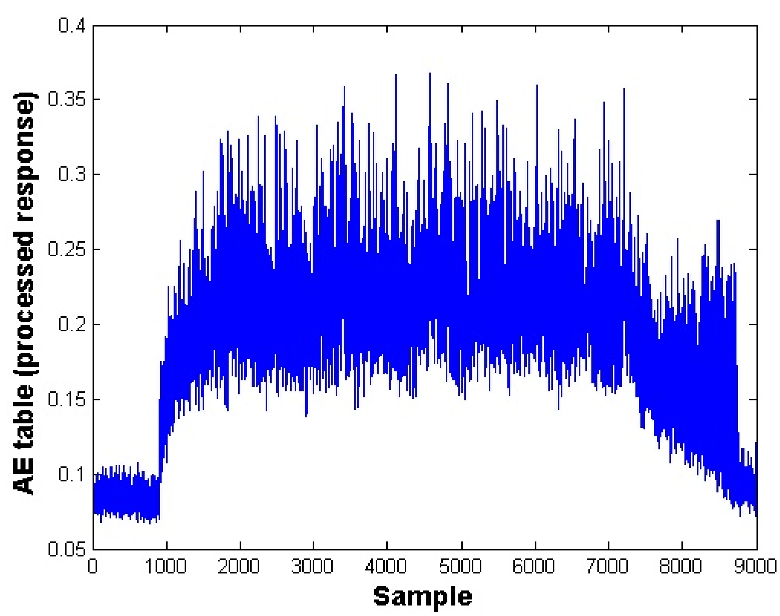

Figure 2.4: Acoustic emission signal (table)

Table 2.2: Experimental conditions

Case	Depth of Cut	Feed	Material
1	1.5	0.5	1 – cast iron
2	0.75	0.5	1 – case iron
3	0.75	0.25	1 – cast iron
4	1.5	0.25	1 – cast iron
5	1.5	0.5	2 – steel
6	1.5	0.25	2 – steel
7	0.75	0.25	2 – steel
8	0.75	0.5	2 – steel
9	1.5	0.5	1 – cast iron
10	1.5	0.25	1 – cast iron
11	0.75	0.25	1 – cast iron
12	0.75	0.5	1 – cast iron
13	0.75	0.25	2 – steel
14	0.75	0.5	2 – steel
15	1.5	0.25	2 – steel
16	1.5	0.5	2 – steel

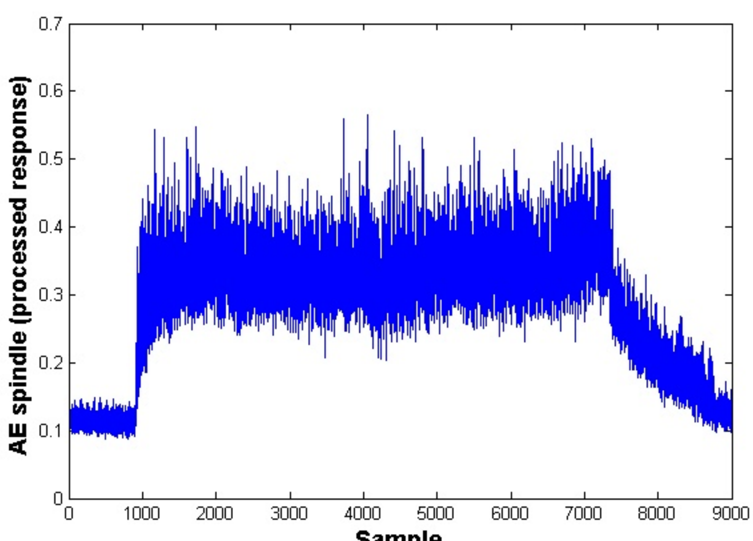

Figure 2.5: Acoustic emission signal (spindle)

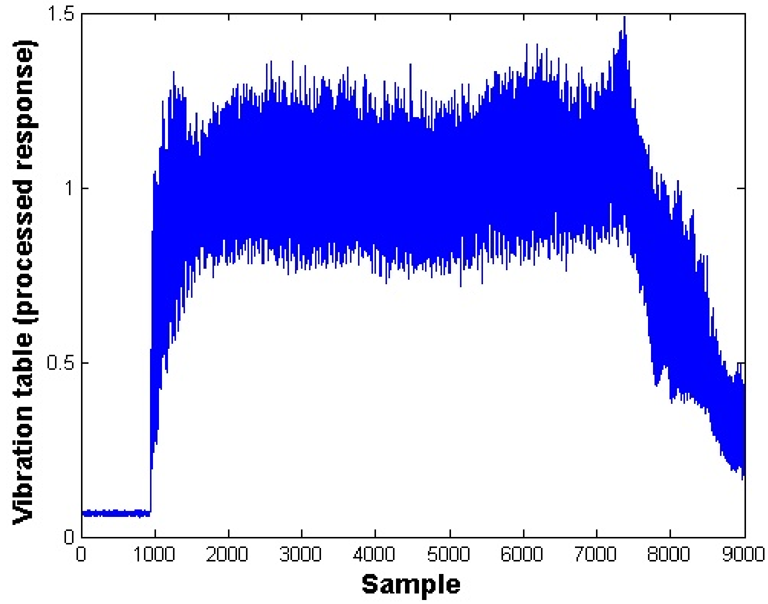

Figure 2.6: Vibration signal (table)

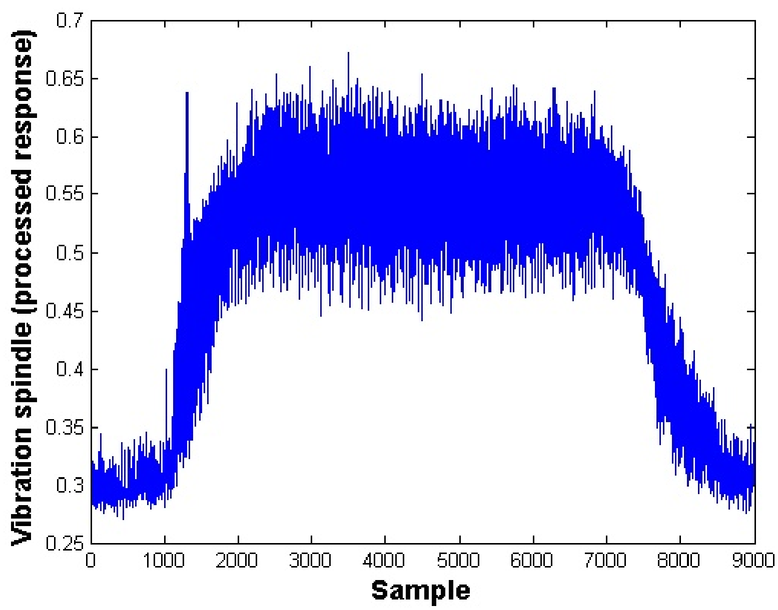

Figure 2.7: Vibration signal (spindle)

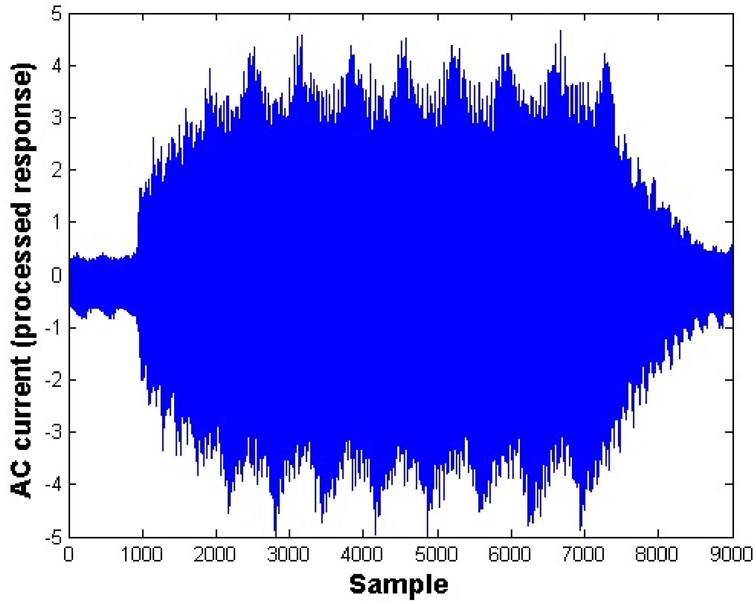

Figure 2.8: Spindle motor current signal

Chapter 3

Sensor Selection/Fusion

3.1 Introduction

If cutting conditions such as machining parameters and machine stiffness change, it can affect the sensitivity and the noise rejection of the sensed signals. Therefore, it is helpful to use more than one sensor in order to increase the reliability of the system and avoid uncertainty. Two strategies for using more than one sensor are using multiple sensors and sensor fusion. Multiple sensors monitoring refers to using more than one sensor but with non-complementary information to increase the reliability. For example, using vibration sensors at different locations and use the combined information for monitoring purpose.

Sensor fusion is to use signals of more than one sensor with complimentary information. Each sensor has some advantages and some disadvantages. A proper sensor fusion approach can assist to benefit from the advantages of different sensors and omit the drawbacks. For example, cutting forces and AE are less correlated and they can be used effectively as complementary information[13].

This research uses vibration signals, AE signals and AC current of the spindle as fault indicators. One of each vibration and AE sensors is located on the table of machining center and the other is mounted on the spindle. Following two important decisions should be made in designing multi-sensors or sensor fusion systems:

1- Which sensors have the most complementary information and can work together perfectly;

2- How the sensors information should be combined for maximum performance and accuracy.

This chapter addresses these questions in the investigated machining tool condition monitoring application.

3.2 Sensor Fusion Methodology

AE signals, vibration signals and spindle motor current signal are used as the input signals for monitoring purpose in this chapter. After the signals are acquired and amplified, they should be converted to the features representing the fault situation in order to make the problem solvable. Due to the time variant nature of faulty signals, time-frequency analysis can reveal valuable information about the system. S-transform as an advanced time-frequency transformation method is used to convert the signal from one dimensional time domain to two dimensional time-frequency domain.

The transformed data to time-frequency domain has high dimensions. This makes the calculation cost high, particularly for online applications in which immediate response is necessary. Moreover, the most relevant data to the faulty situation should be used to eliminate the inaccuracy because of the irrelevant information. A 2D principal component analysis is performed on the data to extract most relevant information and reduce the dimensionality of the data. Based on this technique a group of ranked features are extracted from each signal.

Figure3.1illustrates the methodology from the signal acquisition step to the fault estimation. Three common methods of data fusion are investigated in this study. Figure3.1-a to c represent these three levels of data fusion and their differences.

- Feature level data fusion

In the first approach (Figure3.1-a), feature level data fusion, the outputted ranked features from two indicator signals are combined to form a combined matrix of features and combined features are used for further analysis. Afterwards, the combined features for each case should be compared with the extracted combined features of the machine in normal state. The deviations from the normal situation can be correlated with the fault. A 2D correlation analysis is employed in this step and a correlation score is assigned to each case based on its similarity to normal situation. After obtaining the corresponding correlation scores for each system state, MATLAB curve fitting toolbox is used to determine a model between the correlation scores of each machine state and the corresponding fault values.

- Score level data fusion

Figure3.1-b represents the second sensor fusion technique, score level data fusion. The sensors information in this approach are compared one step later in comparison to previous method. In this system, the correlation of each signal individually evaluated with the same type of signal and under same operation condition but in normal situation. Therefore, two scores are produced based on two input signals. Subsequently, the average of these scores is used as the combined score for the next steps. The same as the first method, a function between the combined scores and their corresponding flank wear values is obtained in the last step of this method.

- Decision level data fusion

In the third technique (Figure3.1-c), decision level data fusion, the signals information does not be combined with each other until the final step. Therefore, a

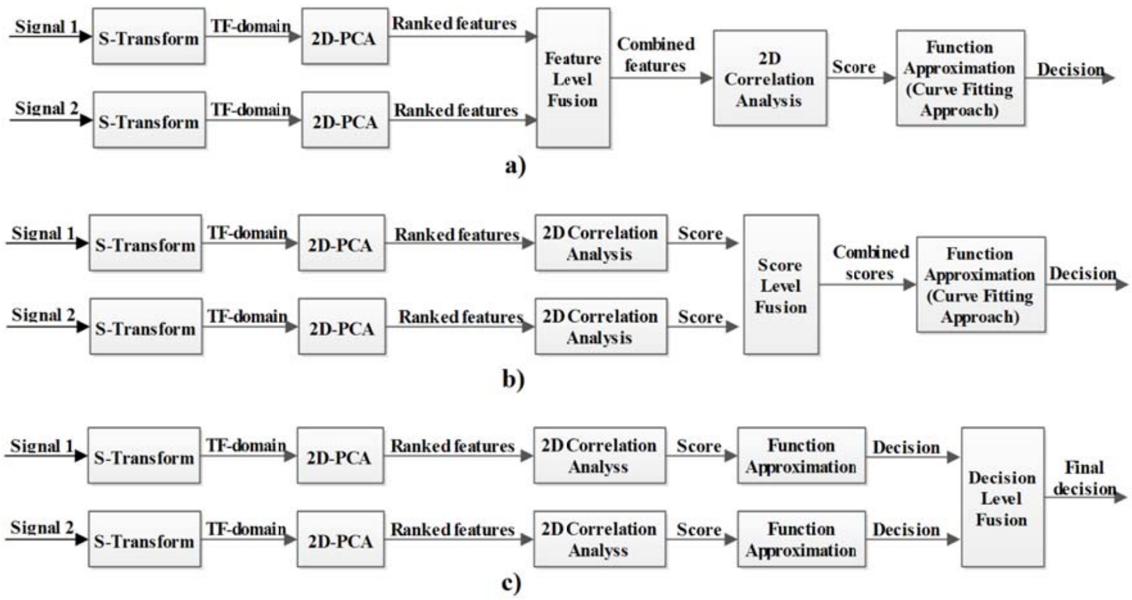

Figure 3.1: Methodology overview: a) Feature level sensor fusion, b) Score level sensor fusion, c) Decision level sensor fusion

system based on each individual signal is designed. After defining a function between tool fault and the correlation score for each signal, the fault value is estimated. Finally, the average of two estimated fault values is used as the tool fault magnitude for decision step.

For each level of data fusion, different pairs of signals are tested and a comparison between the performance of pairs of sensors as well as levels of data fusion is presented in the following sections.

3.3 Background of Techniques

In this section, the algorithms which are used for each step of the monitoring system are presented and the formulation is provided. S-transform is an advanced time-frequency transformation method which is used for converting the signals from time domain to time-frequency domain. S-transform formulation and descriptions are provided in Chapter4along with other time-frequency transformation methods. 2D

PCA is an extension of the original PCA which is implemented in this chapter for dimensionality reduction and the 2D correlation analysis is employed to reflect the similarity of each machine state to the healthy state as a feature extraction method.

3.3.1 2D Principal Component Analysis

Principal component analysis is a classical feature extraction and dimensionality reduction technique widely used in the areas of pattern recognition. In the PCA-based feature extraction, the 2D matrices must be previously transformed into 1D vectors. It is difficult to evaluate the covariance matrix accurately in the high dimensionality due to the large size and the relatively small number of training samples. 2D PCA extends the original PCA to be capable of working directly with the original matrix rather than its vectored sample. As a result, it is easier to evaluate the covariance matrix accurately in 2D PCA and less time is required to determine the corresponding eigenvectors[55]. 2D PCA algorithm is defined as follows:

Assume a training set of 2D matrices $\{X_1, X_2 \ldots X_N\}$, 2D PCA first constructs the total covariance matrix G_t using all the training samples[56].

$$G_t = \sum_{i=1}^{N} \left(X_i - \bar{X} \right)^T \left(X_i - \bar{X} \right), \tag{3.1}$$

where N is the number of training samples, X_i is the ith training sample and $\bar{X}$ is the mean of all training samples. The projection axes of 2D PCA, $W_1, W_2, \ldots, W_D$, can be achieved by calculating maximal value of the sample scatter criterion.

$$j\left(W\right) = W^T G_t \, W, \tag{3.2}$$

where W is a unitary column vector. Actually, $W_1, W_2, \ldots, W_D$ are the eigenvectors corresponding to maximal eigenvalue of G_t. Finally the features can be extracted based on following equation:

$$Y = X\, W_{opt}, \tag{3.3}$$

where

$$W_{opt} = [W_1, W_2, \ldots, W_d], \tag{3.4}$$

3.3.2 2D Correlation Analysis

Tool faults such as flank wear cause some abnormality in the acquired signal of the machine. Therefore, a similarity analysis between the acquired signals from machine actual state and the ideal healthy state can represent the system condition. To evaluate this, a 2D correlation analysis between the machine state and the ideal state is implemented. As the fault value increases in the system, the indicator signals show more deviation from the healthy situation and the correlation coefficient decreases. The correlation coefficient approaches to 1 if two signals are more similar. The correlation coefficient between two matrices A and B (transformed signals to time-frequency domain) can be derived based on the following equation:

$$r = \frac{\sum_m \sum_n \left(A_{mn} - \overline{A}\right)\left(B_{mn} - \overline{B}\right)}{\sqrt{\left(\sum_m \sum_n \left(A_{mn} - \overline{A}\right)^2\right)\left(\sum_m \sum_n \left(B_{mn} - \overline{B}\right)^2\right)}} \tag{3.5}$$

where $\overline{A}$ and $\overline{B}$ are the mean value of A and B, respectively.

3.4 Sensor Fusion Results

The important question in using more than one sensor is that which sensors can provide more complementary information and work effectively together in a system to increase accuracy and reliability of the monitoring system. In this step score level sensor fusion methodology (Figure3.1-b) is implemented and many combination pairs of signals are tested as the input of systems. Each table from3.1to3.5 represents the combination of one signal with all the other available signals in the dataset. All possible multi-sensor and sensor fusion as well as single input systems are investigated and compared in this section.

Table3.1provides the fault estimation errors for the systems which work with combination of AE of table signal with other available signals. When AE of table is used individually, the mean error and maximum error of corresponding monitoring systems are 8.65% and 16.52% respectively. When two AE sensors are used together in a system, the mean error is decreased to 5.91% and maximum error is decreased to 10.14%. This suggests that using multiple AE sensors can improve the accuracy of the system. The best accuracy is achieved with the fusion set of AE table sensor and vibration spindle sensor. Mean error of this case is 4.28% which is less than half of using just one sensor. It can be also interpreted from this table that if acoustic emission of table is used as the first signal in fusion, it is better that the other sensor such as vibration be mounted on the spindle of the machining center.

Table 3.1: Score level sensor fusion for AE of table with other signals

AE table	No fusion	AE spindle	Vib table	Vib spindle	AC current
Mean error	8.65	5.91	7.57	4.82	8.36
Max error	16.52	10.14	13.57	8.57	13.36

The fusion information of AE of spindle signal with the other available signals is provided in Table3.2. The best results is achieved by fusion of this signal with AC current signal. The error of fault estimation can decrease to 2.67% mean error and 5.9% maximum error which is a robust accuracy for practical usage. It should be noted that for some fusion of signals, if the provided information are not complimentary, it can even deteriorate the results. For example using just AE of spindle provides more accurate information in comparison to AE of spindle and table together. However, in the case that one of the sensors fails, the other sensor can still assure the reliability. It is worth to mention that combining AE spindle and vibration table gives more accurate results in comparison to combining AE spindle with the vibration sensor at the same location, i.e., spindle. It implies that in using more than one sensor it is appropriate to locate the sensors in different positions.

Table 3.2: Score level sensor fusion for AE of spindle with other signals

AE spindle	No fusion	AE table	Vib table	Vib spindle	AC current
Mean error	3.9	5.91	3.77	4.25	2.67
Max error	8.25	10.14	8.78	9.31	5.9

Based on Table3.3, for vibration signal at table of machining center, the best fusion set result is obtained by combining it with the AE of spindle. In this case, 3.77% for mean error and 8.78% for maximum error are obtained. It is worthwhile to note that fusion of the vibration signal of the table with AE of the spindle can increase the accuracy around 5 times (from 16.99% to 3.77%). However, using multiple vibration sensors cannot improve the results significantly. This table also suggests that the combination of information of a sensor mounted on the table with another mounted on the spindle gives better results than both of them mounted at the same place.

Table 3.3: Score level sensor fusion for vibration of table with other signals

Vib table	No fusion	AE table	AE spindle	Vib spindle	AC current
Mean error	16.69	7.57	3.77	15.89	11.94
Max error	25.44	13.57	8.78	23.33	14.96

The information for combination of vibration of spindle signal with other signals is provided in Table3.4. While all the fusion sets improve the results significantly and decrease the error to less than half, using multiple sensors of vibration do not improve the results. The lowest fault estimation mean error is achieved by the combination of vibration of spindle and AE of spindle signals (4.25%). However, the lowest maximum error is achieved by the combination of vibration of spindle and AE of table signals (8.57%). The table information implies that AE signal is a good candidate to use with vibration signal.

Table 3.4: Score level sensor fusion for vibration of spindle with other signals

Vib spindle	No fusion	AE table	AE spindle	Vib table	AC current
Mean error	11.46	4.82	4.25	15.89	5.9
Max error	18.19	8.57	9.31	23.33	12.15

Table3.5presents the information for AC current of spindle signal. While its individual accuracy is not high with mean error of 15.9%, combining it with other signals can increase the accuracy and decrease the error rate significantly. The combination of AC current and table AE reduces the fault estimation error by 7.5%. The best accuracy is obtained by the fusion of AC current and AE of spindle. The fusion of AC current signal gives better results when the other sensor is mounted on the spindle. Based on the results, while the AC current sensor has not robust accuracy to be used individually, it can give accurate results when it is combined with another signals. The industrial applicability and cost efficiency of this sensor also encourage using this signal as a complimentary information in sensor fusion systems.

With an overall view of Tables3.1to3.5, best accuracy can be reached by fusion of AC current signal and AE of spindle. Generally, combination of AE and vibration signals gives better results when one of them is mounted on the table and another on the spindle rather than both of them in the same place. AC current sensor is also improved the accuracy when it is fused with another signal in all experiments

Table 3.5: Score level sensor fusion for AC current with other signals

AC current	No fusion	AE table	AE spindle	Vib table	Vib spindle
Mean error	15.9	8.36	2.67	11.94	5.9
Max error	45.43	13.36	5.9	14.96	12.15

and can be an ideal choice for sensor fusion although it has not provided promising results individually. Additionally, using multiple sensors did not improve the results significantly in comparison to selecting the proper fusion set.

3.5 Comparison Between Different Levels of Data Fusion

Data fusion based monitoring techniques combine data from different sources to achieve best accuracy and reliability. In designing a sensor fusion method, it is important to determine in which level of process the signals information should be combined. In this section, three practical levels of data fusion are implemented and compared. Figure3.1(a to c) explains these approaches.

The first method is feature level fusion. In this method, the outputs of 2D PCA for both signals are used to form a combined feature vector. This method can be considered as a combination of the raw data or not highly processed data from different sources. After combining the data at this level, it will be determined that how much this new combined feature vector is deviated from the feature vector obtained by the same fusion technique and signals but in normal situation. A score will be assigned to fusion set based on the result of this correlation analysis and a monitoring algorithm is designed bades on that score.

The second approach is score level fusion. In the score level fusion, the output of

Table 3.6: Mean and maximum fault estimation errors for systems designed with feature, score and decision level data fusion

Signal pairs	Feature level fusion		Feature level fusion		Decision level fusion	
	Mean err	Max err	Mean err	Max err	Mean err	Max err
AE table & AE spindle	5.63	12.08	5.91	10.14	6.28	10.05
AE table & Vib table	16.54	26.18	7.57	13.57	6.07	9.74
AE table & Vib spindle	8.6	15.85	4.82	8.57	5.62	10.78
AE table & AC current	15.6	44.01	8.36	13.36	9.39	24.15
AE spindle & Vib table	15.88	24.3	3.77	8.78	6.42	8.6
AE spindle & Vib spindle	4.84	9.11	4.25	9.31	5.59	9.16
AE spindle & AC current	15.02	41.44	2.67	5.9	8.72	26.29
Vib table & Vib spindle	16.97	24.13	15.89	23.33	11.9	19.25
Vib table & AC current	18.48	42.1	11.94	14.96	10.71	15.04
Vib spindle & AC current	15.77	44.93	5.9	12.15	13.68	27.06
Average error	15.66	25.24	5.91	11.15	7.57	12.91

2D PCA is compared with the healthy state output using 2D correlation analysis for each signal and a correlation score is assigned to each signal individually. Afterwards, the obtained scores from each signal are integrated and the average of them is used as the combined score.

In the third method, decision level fusion, each signal estimates the fault individually and the average of estimations is used as the final fault value. These three methods are implemented and tested with all dataset signals. Table3.6provides the information of fault estimation mean and maximum errors for the dataset fusions. The last row is the average of these errors in all the cases.

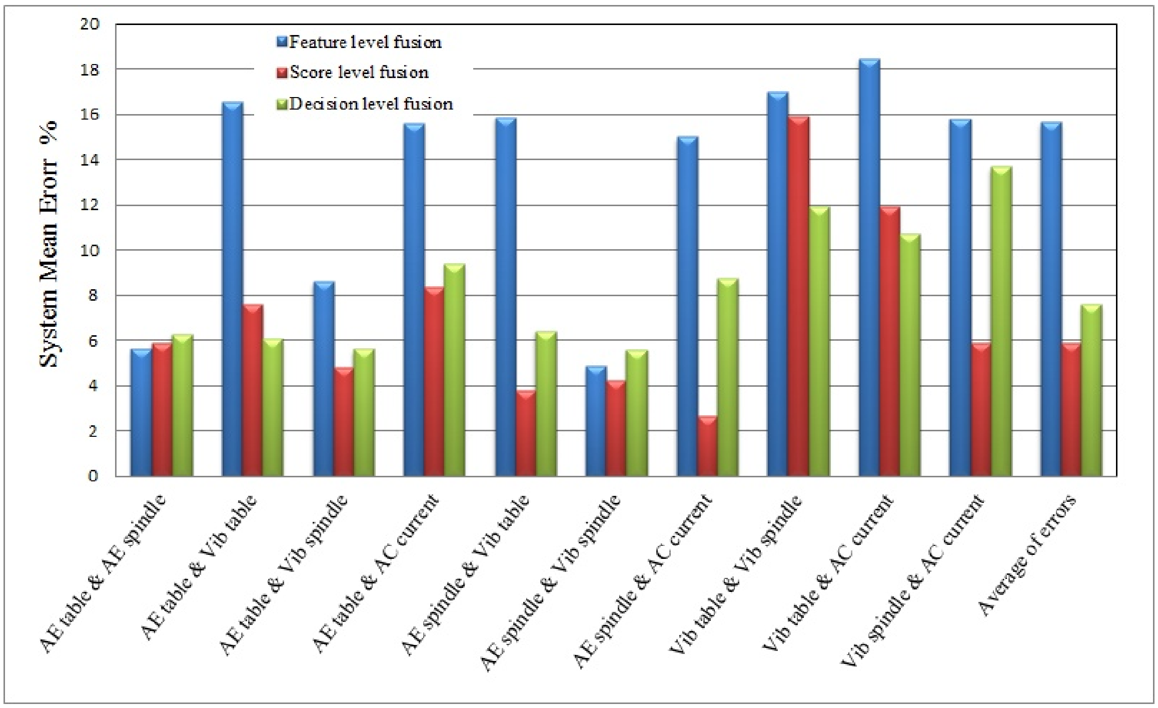

Figure 3.2: Comparison between mean percentage error of systems designed with different data fusion techniques for various sets of input signals

It is implied from this table that score level data fusion method outperform the other two methods while decision level fusion provides lower error in comparison to feature level fusion. Figure3.2illustrates the detection mean error results for different signal pairs and different fusion levels. Blue bars represent feature level fusion, red bars represent score level and green bars represent decision level fusion. It is clear from the graph that in most cases and also in average of errors, score level fusion outperforms the other two data fusion level methods. It can be explained as in feature level data fusion, the information is comparatively raw and combining the data at this level may end up in loosing some information. In other words, it is too early to combine the data at this stage. In decision level data fusion, however, the datasets are combined too late and after many filtrations. Score level may be ideal as it combines the data at an appropriate time.

3.6 Chapter Summary

In this chapter, sensor fusion based flank wear monitoring in milling operation is investigated. S-transform is employed to convert the signals from time domain to time-frequency domain and 2D PCA algorithm decreases the dimensionality of the S-transform outputs and provides ranked features. Many pairs of signals are fed into the system in each fusion scenario and the monitoring and fault estimation accuracy results for different signal pairs are compared together and also with the results obtained from a single signal input.

In another experiment, the signals information are combined together at three different levels, feature level, score level, and decision level, and the performance of each fusion level is evaluated and compared with others.

It is observed from Table3.1to Table3.5that the highest accuracy can be achieved with the AE of spindle and AC current with the mean detection error of 2.67% and maximum fault estimation error of 5.9% in score level fusion. Vibration and current signals both can be good candidates to be combined with AE signal for sensor fusion.

In using two different sensors such as vibration and AE, it is better that one of them be mounted on the spindle and the other on the table of the machining center rather than both of them at the same place. Moreover, AC current signal is a perfect candidate to be fused with the other signals based on its low cost and the complementary information it can provide for other signals and it can improve the accuracy significantly. However, employing this signal individually in a monitoring system may not be reliable since the maximum error reaches to 45.43% in this experience.

In contrast, AE and vibration signals can be used individually as fault indicator signals with acceptable results. AE signal is also a candidate with high potential for sensor fusion with vibration and AC current as its less correlated nature to them. Furthermore, while well selected sensor fusion can improve the monitoring system accuracy significantly, using multiple sensors from the same type has not a significant effect on the system.

Comparison between different levels of fusion also suggests that score level sensor fusion has best accuracy for this design with average mean and maximum monitoring errors of 5.91% and 11.15% respectively. Decision level sensor fusion has also better performance than feature level fusion.

Chapter 4

Time-Frequency Signal Processing

4.1 Introduction

Acquired signals in industrial environment have a significant noise level. Moreover, changes in the signal pattern can be due to various reasons such as a change in operation condition or different source of faults. Furthermore, faulty signals usually have a time variant nature. Therefore, time-frequency analysis is an effective approach for tool condition monitoring based on its ability to reveal time variant characteristics of the signal as well as identifying the signal's frequency components.

In this chapter, a comparative study between performance of five time-frequency transformation methods in tool condition monitoring application is conducted. The definition and formulation of the time-frequency transformations which are used in this research are explained in the next section. Results section reports the performance of each method in terms of mean and maximum error of fault estimation.

The structure of the designed systems in this chapter are presented in Figure 4.1. The systems are tested for all available signals in the dataset. In each system, one signal is inputted to the system and after pre-processing, a time-frequency transformation is conducted. In the next step, 2D PCA and correlation analysis converts data from time-frequency domain to feature space. 2D PCA decreases the dimensions of time-frequency output and provides the principal components of the time-frequency matrix. Afterwards, the correlation analysis compares the results with the results of a healthy signal in the same operation conditions and assigns a score to the signal. This method assigns 1 to a signal when the signal is exactly similar to the healthy case signal and the score decreases as the signal deviates from normal signal. Finally a curve is obtained based on the derived scores and their corresponding fault values using MATLAB. This curve is used to estimate faults values for future signals.

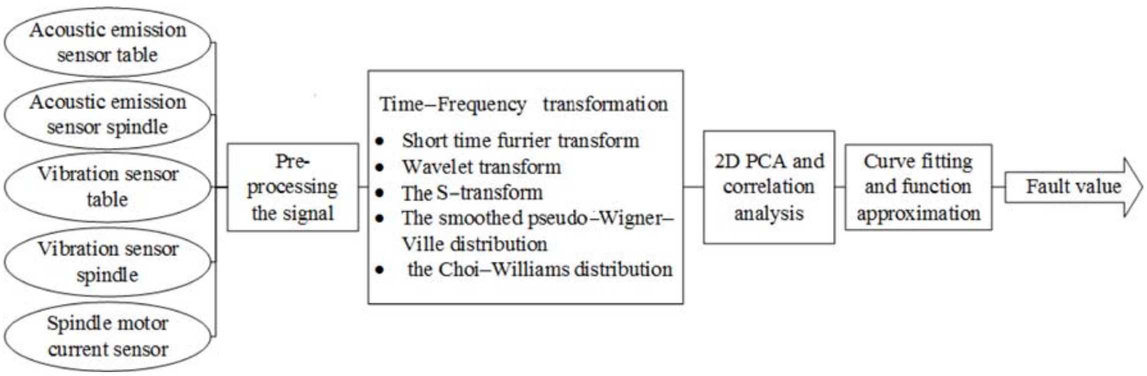

Figure 4.1: Monitoring systems structure with various time-frequency methods and different sets of input signals

4.2 Background of Techniques

4.2.1 Short Time Fourier Transform (STFT)

Short time Fourier transform represents the time-varying characteristics of a signal by adding a time variable to the traditional Fourier spectrum. It assumes that in a short duration, the segmented signal can be assumed to be stationary due to minor changes. After defining the window function and its length, this method's time-frequency resolution is fixed. In practice, for higher frequency components, a shorter time window should be implemented and vice versa. Heisenberg uncertainty principle determines that the best time location and the frequency resolution cannot be obtained at the same time. Therefore, this method lacks adaptability and it is not suitable to analyze highly transient phenomena in signals, like impulses[41]. Equation (4.1) represents continuous expression of STFT[57].

$$STFT_x(t,\nu,h) = \int_{-\infty}^{+\infty} x(u)\, h^*(u-t)\, e^{-j2\pi\nu u} du \tag{4.1}$$

where $h(t)$ is a short time analysis window localized around $t=0$, $\nu=0$. Figure 4.2 represents the STFT of the acoustic emission signal at spindle for a healthy signal and a signal with Vb = 0.65 state.

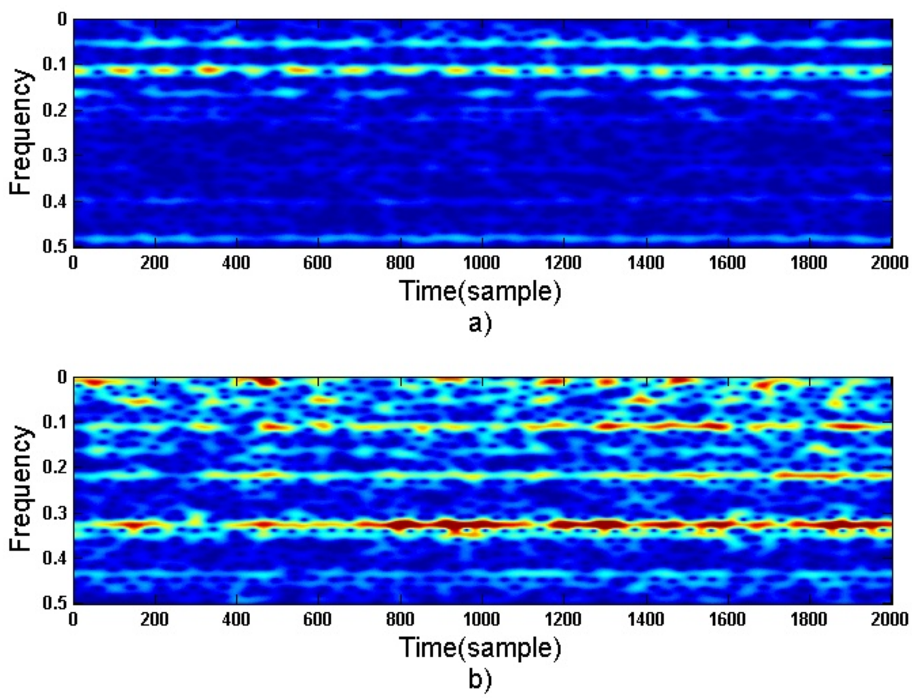

Figure 4.2: STFT representation of spindle AE signals: a) Vb = 0 and b) Vb = 0.65.

4.2.2 Wavelet Transform (WT)

Wavelet transform is widely used for health condition monitoring systems in the literature. In the wavelet transform, wavelets are used as the basis instead of sinusoidal functions. It is an effective tool for transient signal analysis as well as time-frequency localization since, it adds a scale variable in addition to the time variable in the inner product transform. It has a better time localization but a lower frequency resolution for higher frequency components. In contrast, for lower frequency components, the frequency resolution is higher while the time localization is worse. Equation (4.2) describes the formulation of the continuous wavelet transform[41].

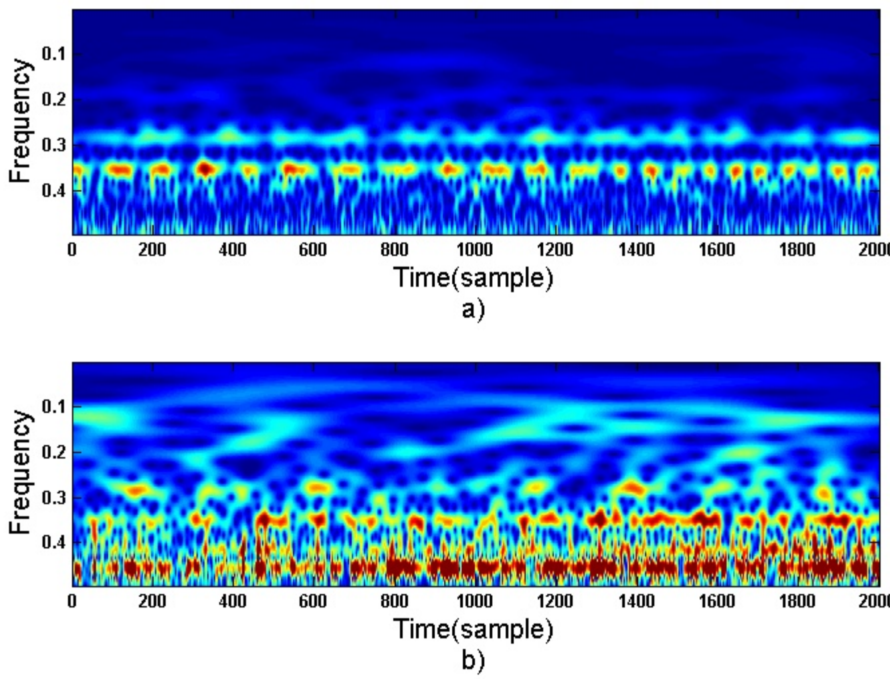

Figure 4.3: WT representation of spindle AE signals: a) Vb = 0 and b) Vb = 0.65.

$$WT_x(t,a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(u)\,\psi\frac{(u-t)}{a}\,du \tag{4.2}$$

where wavelet $\psi(u-t)/a$ is derived by dilating and translating the wavelet basis $\psi(t)$, $1/\sqrt{a}$ is a normalization factor to maintain energy conservation and $a > 0$. Figure4.3depicts the WT of the acoustic emission signal of spindle for a healthy signal and a signal with Vb = 0.65.

4.2.3 S-Transform (ST)

S-transform is an advanced time-frequency transformation with a great ability to interpret from low quality signals. This method can be considered as an extension of the continuous wavelet transform (CWT) concept known for its local spectral phase properties. A localizing Gaussian window is employed in this method in a way that while the localizing scalable Gaussian window dilates and translates, the modulating sinusoids are fixed with respect to the time axis[58].

The employed window function in S-transform technique is a function of both time and frequency which is the advantage of S-transform in comparison to STFT. Due to this property, the window is wider in the time domain for lower frequencies, and narrower for higher frequencies. Therefore, the window can provide good localization in the time domain for high frequencies, while it provides good localization in the frequency domain for low frequencies[59].

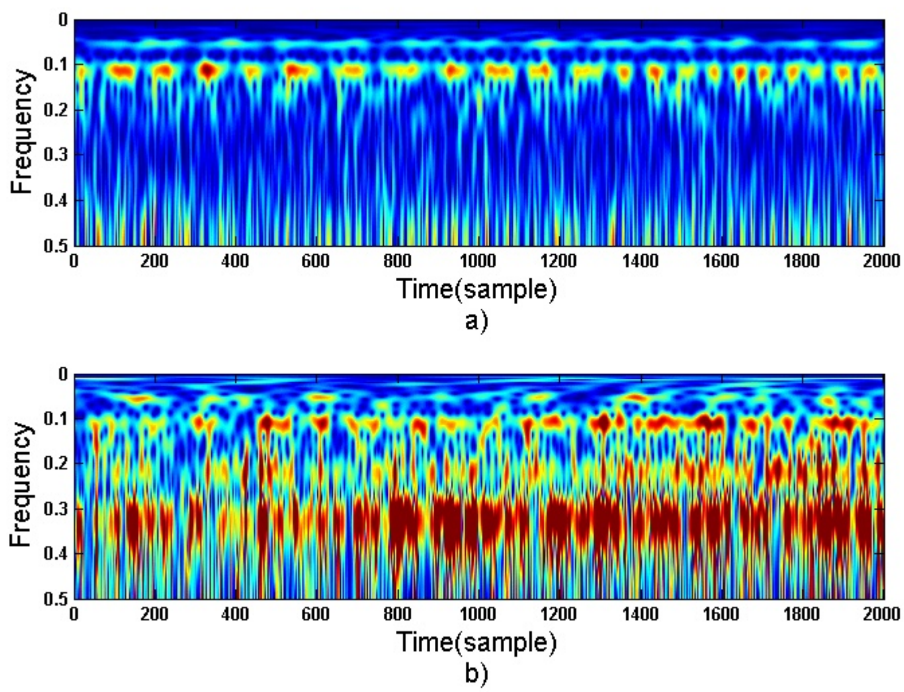

Figure 4.4: ST representation of spindle AE signals: a) Vb = 0 and b) Vb = 0.65.

Continuous S-transform of a time dependent function of $h(t)$ is defined as follows[60].

$$S\ (\tau, f) = \int_{-\infty}^{\infty} h\,(t)\ \frac{|f|}{\sqrt{2\pi}}\ e^{-(\tau-t)^2 f^2/2}\ e^{-i2\pi f t}\ dt \tag{4.3}$$

There are computational advantages to use the equivalent frequency domain definition of the S-transform for the discrete case. It can be defined as[60]:

$$\begin{aligned} &\mathrm{S}\left[jT, \tfrac{n}{NT}\right] = \sum_{m=0}^{N-1} H\left[\tfrac{m+n}{NT}\right] e^{-2\pi^2 m^2/n^2} e^{i2\pi m j/N}, n \neq 0 \\ &\mathrm{S}[jT, 0] = \tfrac{1}{N} \sum_{m=0}^{N-1} h\,[mT]\,, n = 0 \end{aligned} \tag{4.4}$$

where H[n/NT] is the Fourier transform of the N-point time series h[kT] and j,m, and $n = \{0, 1, ..., N-1\}$. Averaging the S-transform over time to get the Fourier transform spectrum, and inverting to the time domain gives the discrete inverse of the S-transform as follows[60]:

$$h\,[kT] = \sum_{n=0}^{N-1} \left\{ \frac{1}{N} \sum_{j=0}^{N-1} S\left[jT, \frac{n}{NT}\right] \right\} e^{\frac{i2\pi nk}{N}} \tag{4.5}$$

Figure4.4shows the ST representation of the acoustic emission signal of spindle for a healthy signal and a signal with Vb = 0.65.

4.2.4 Smoothed Pseudo-Wigner-Ville Distribution (PW)

Smoothed Pseudo-Wigner-Ville distribution belongs to bilinear time-frequency distribution category which represents the signal energy distribution in the joint time-frequency domain. The basis of almost all the bilinear time-frequency distributions is the Wigner-Ville distribution. It has a high time-frequency resolution, however, the drawback of this method is that for multi-component signals, it suffers from the inevitable cross-term interferences. To overcome this problem, Cohen class distributions are proposed to obtain the expected properties like higher resolution, non-negativity and removal of cross terms by smoothing the Wigner-Ville distribution through time and frequency shifting with a kernel function[41]. Smoothed Pseudo-Wigner-Ville distribution is one of these modified methods. Equation (4.6) presents this transformation equation[61]:

$$\mathrm{PW_x}(\mathrm{t},\nu) = \int_{-\infty}^{+\infty} \mathrm{h}(\mathrm{u})\,\mathrm{x}(\mathrm{t}-\mathrm{u}/2)\,\mathrm{e}^{-\mathrm{j}2\pi\nu\mathrm{u}}\mathrm{du} \tag{4.6}$$

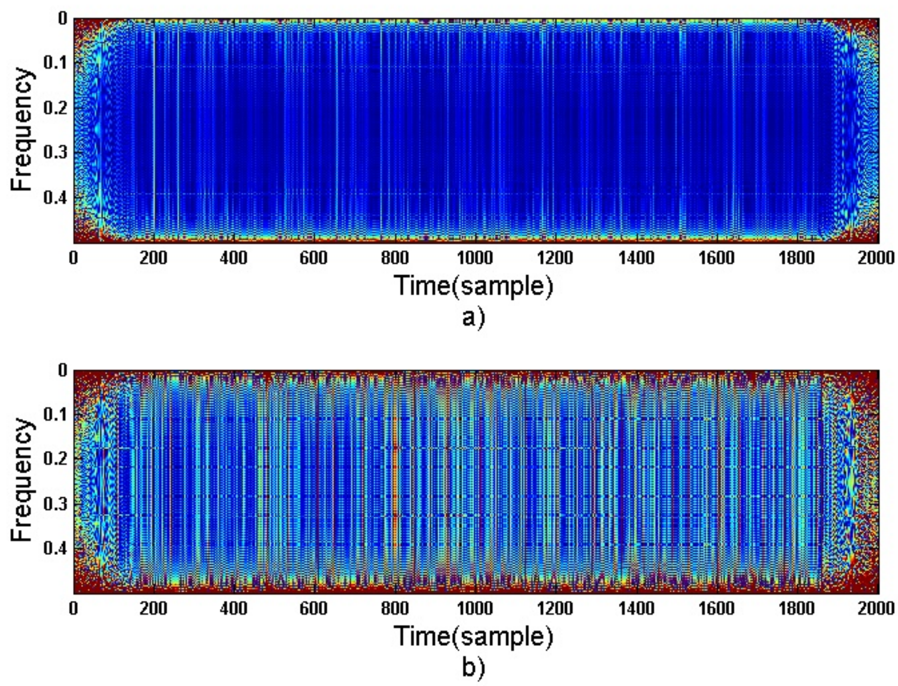

Figure 4.5: PW distribution of spindle AE signals: a) Vb = 0 and b) Vb = 0.65.

Figure4.5represents the PW distribution of the acoustic emission signal of spindle for a healthy signal and a signal with Vb = 0.65.

4.2.5 Choi-Williams Distribution (CW)

Choi-Williams distribution is also a time-frequency distribution which uses an exponential kernel function for smoothing the Wigner-Ville distribution. The kernel function is fixed and it determines the ability to suppress cross-terms. However, suppressing cross-terms with a time-frequency smoothing kernel function often deteriorate time-frequency resolution and it may also create extra interferences[60]. Equation (4.7) express the formulation of this distribution[62]:

$$CW_x(t,\nu) = 2\int\int_{-\infty}^{+\infty} \frac{\sqrt{\sigma}}{4\sqrt{\pi|u|}} e^{-\frac{\vartheta^2\sigma}{16u^2}} \mathrm{x}\left(t+\vartheta+\frac{u}{2}\right) x^*\left(t+\vartheta-\frac{u}{2}\right) e^{-j2\pi\nu u} d\vartheta du \quad (4.7)$$

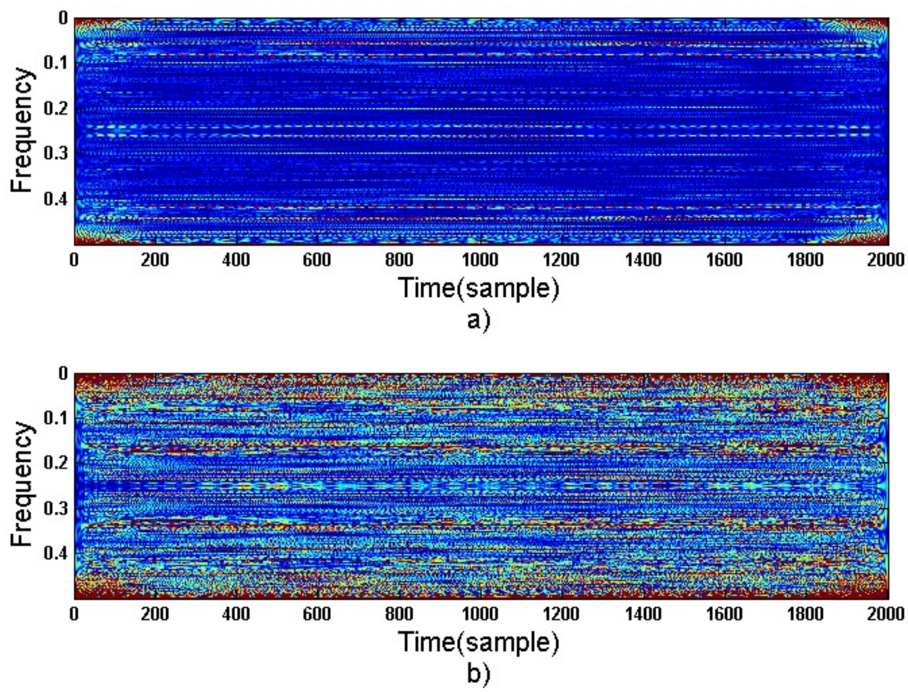

Figure 4.6: CW distribution of spindle AE signals: a) Vb = 0 and b) Vb = 0.65.

Figure4.6illustrates the CW distribution of the acoustic emission signal of spindle for a healthy signal and a signal with Vb = 0.65.

4.3 Comparison between Time-Frequency Transformation Methods

This section provides a comparison between monitoring systems each are made based on one set of dataset input signals (AE at table, AE at spindle, vibration at table, vibration at spindle and AC current of the spindle motor) and one of the time-frequency transformation methods. For each system, 80% of the available signals are used as the training dataset and 20% as the test dataset. For the training signals, the correlation scores with normal case are extracted and a model is derived between the scores and corresponding fault values using MATLAB curve fitting toolbox. Afterwards, a set of unseen signals called test signals are fed into the system and the fault values are estimated based on the derived model. Finally the estimated faults of the test dataset are compared to the actual experimental values and mean error and maximum error are calculated.

Table 4.1: Mean error for different time-frequency transformation techniques

Mean Error Percentage	STFT	Wavelet transform	S-transform	Smoothed pseudo-Wigner-Ville distribution	Choi-Williams distribution
AE table	10.04	10.53	7.51	10.29	10.39
AE spindle	10.3	8.89	9.04	11.03	11.17
Vibration table	17.74	16.45	14.55	15.68	17.32
Vibration spindle	15.8	12.35	14.93	14.14	12.24
AC current	8.07	7.59	5.57	15.18	9.85
Average	12.39	11.16	10.32	13.26	12.19

Table4.1presents the mean error and Table4.2presents the maximum error of

fault estimation in each monitoring system. Based on Table4.1, ST has the lowest mean error in almost all the scenarios. Wavelet transform as a widely used technique for condition monitoring also shows promising fault estimation accuracy. Last row of the table shows the average error based on all the systems. It reveals that ST has the minimum average of mean errors (10.32%) among all transformation methods. WT is in the second place with 11.16%. The other three methods also provide acceptable results for practical purposes.

Table 4.2: Maximum error for different time-frequency transformation techniques

Maximum Error Percentage	STFT	Wavelet transform	S-transform	Smoothed pseudo-Wigner-Ville distribution	Choi-Williams distribution
AE table	21.45	22.56	19.85	29.24	28.1
AE spindle	25.66	26.41	24.59	18.18	21.21
Vibration Table	30.88	29.92	28.43	39.86	29.23
Vibration spindle	29.27	23.6	39.39	32.16	26.31
AC current	20.45	20.6	12.12	28.38	17.05
Average	25.54	24.62	24.87	29.56	24.38

Maximum error is also calculated as a representative of the system reliability and presented in Table 4.2. All the maximum errors are around 24 to 25 percent except smoothed Pseudo-Wigner-Ville distribution maximum error which is around 29.5%. Figure4.7compares the mean error of systems for different time-frequency transformation methods and input signals.

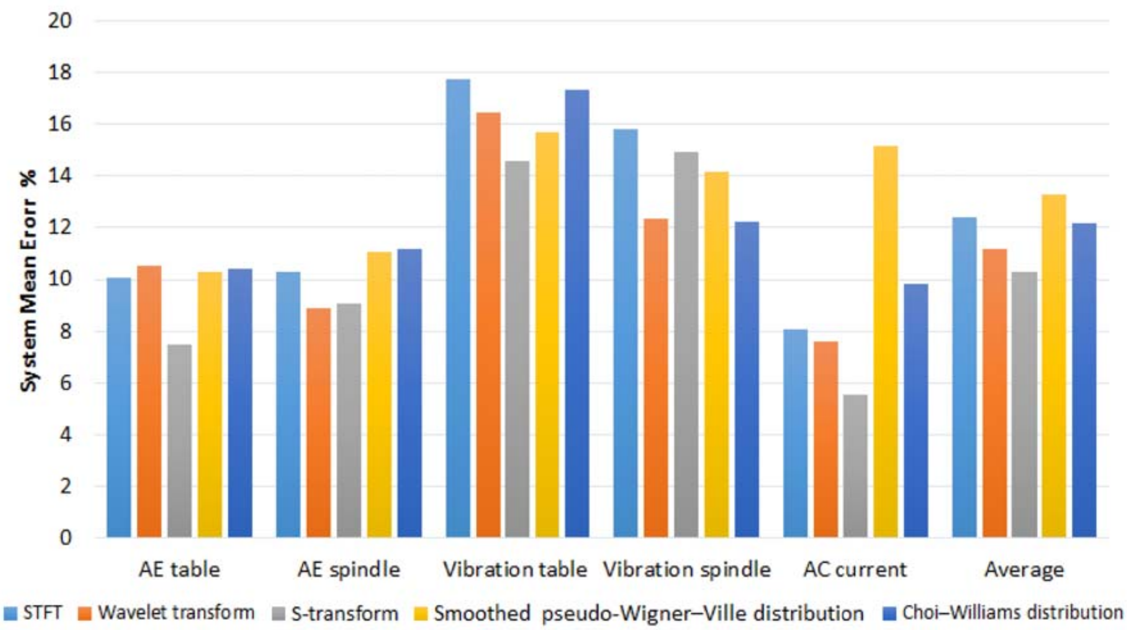

Figure 4.7: Fault estimation mean error of different time-frequency transformation methods.

4.4 Chapter Summary

In this chapter, tool condition monitoring using time-frequency transformation methods is investigated. All dataset input signals are utilized individually as the fault indicators. Three linear popular time-frequency methods in condition monitoring application, STFT, WT and ST, and two bilinear time-frequency distribution, smoothed Pseudo-Wigner-Ville and Choi-Williams are employed for signal processing step.

The accuracy of fault detection in the monitoring systems are acceptable in all the systems which implies solid monitoring systems can be achieved using time-frequency transformation. This enforces the applicability of time-frequency analysis as a promising approach for tool condition monitoring.

It is observed that the best time-frequency transformation method in this study is ST. Wavelet transform also shows promising results and as a widely used technique for condition monitoring is the runner-up. The other three methods also provide acceptable results for practical purposes. Maximum error is also calculated for each scenario which can be a representative of system reliability. Average of maximum errors for each transformation method is about 25% except PW with an average of 29.56%.

Chapter 5

Feature Extraction/Selection

5.1 Introduction

After transferring the faulty signal to time-frequency domain, an important issue for using the information is the high dimensions of the output which makes an interpretation of the signal time-consuming and inappropriate for online application. Moreover, low quality signals may deteriorate the fault detection performance due to noise in the time-frequency domain. Therefore, extracting discriminative features with low dimensions which provides a robust representation of variable of interest (in this case: tool wear) and be relatively invariant to other process variables is an helpful solution. This chapter proposes a feature selection method based on a local region of interest with most informative data in time-frequency domain rather than using the entire information. This approach can be suitable to overcome the aforementioned issues. It can improve the signal resolution as well as reducing the computational cost. This chapter attempts to address the question of how to select this most informative area for this application.

5.2 A Novel Feature Generation Method in Time-Frequency Domain

This section presents a novel method proposed by this research for dimensionality reduction of the output of time-frequency domain information. Let us assume that it is expected to design a monitoring system which works with AE of spindle signal as the fault indicator. Figure5.1(a to c) demonstrates the AE signals for three sample fault values in time domain. It is visible the Figure5.1that as the fault value increases, more deviation is observed from normal situation, especially in the amplitude of the signals.

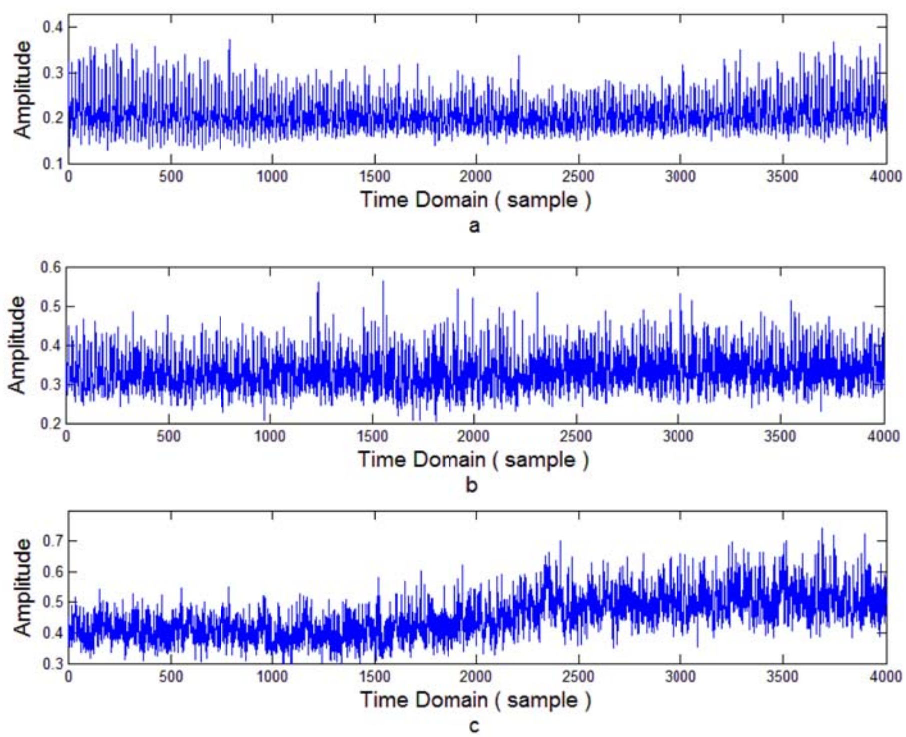

Figure 5.1: Spindle AE signal in time domain: a) Vb = 0, b) Vb = 0.24, and c) Vb = 0.50.

Time-frequency transformation has a high potential to reveal a fault in a signal as faults show their characteristics better in certain frequency ranges. A frequency analysis is helpful to search for a fault signature around an appropriate frequency band which for tool faults is usually around tooth pass frequency. With this approach, one can focus only on the data which is related to tool faults and omit unnecessary information of the environment and other equipments. For example, for monitoring vibration signals, final signal is an accumulation of vibrations from different sources and frequencies. However, only the changes in the vibration signals due to tool faults is important for tool condition monitoring purpose. This makes an frequency analysis helpful to provide the desired information. Faulty signals are also mostly non-stationary and an analysis of the signal changes over time is beneficial for revealing the system's information. Therefore, time-frequency analysis can provide the necessary information for fault monitoring in both time and frequency domains simultaneously, which makes it an ideal approach for signal processing step.

A time-frequency analysis using S-transform is provided in Figure5.2(a to c) for the same signals of the previous figure. The colors change from lower values (blue) to higher values (red) in the graphs for different frequencies and fault values. As the fault value (Vb) increases in the system, higher values for transformation output is observed in certain frequencies. The fault occurrence and growth are well reflected with comparing these graphs. However, an automated approach to convert the visualized data to simple informative values for further analysis and decision making is in demand. Moreover, there are large amount of information which may be unnecessary for monitoring analysis. This method should select the most informative region of data to represent fault values. A method which provides a smaller amount of data with most relevance to the monitoring goal has many benefits like less computational cost and noise rejection capability. This research proposes to extract a local region of time-frequency domain information and use that as the representative of entire information.

Local feature extraction has many advantages such as focusing on the desired

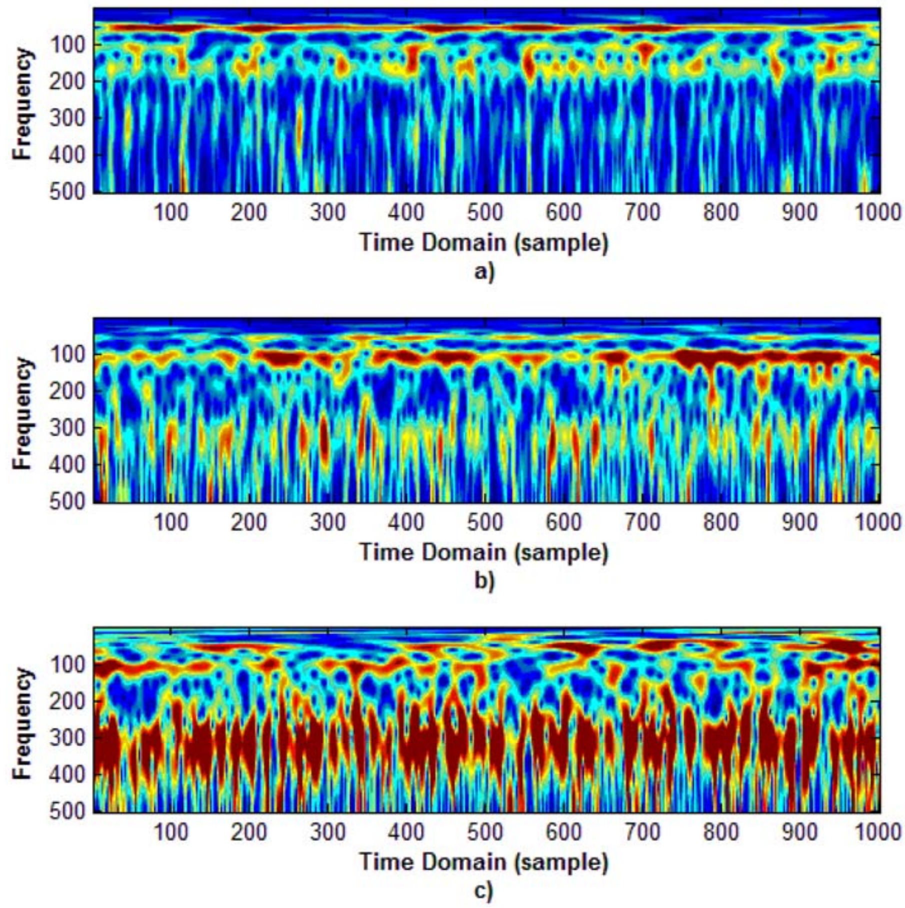

Figure 5.2: Spindle AE signals in time-frequency domain: a) Vb = 0, b) Vb = 0.24, and c) Vb = 0.50.

variables, low calculation cost and neglecting some of the undesirable noise. This local region should not disregard any important information. To fulfill this purpose, a local region with most informative information should be selected. Then the question is how to find the location and size of this local region. An issue with finding this region is that it is really dependent on the application. This section explains the method of this research to find this region.

Let us assume that the local region in time-frequency domain has the τ_1 and τ_2 boundaries in time domain and γ_1 and γ_2 boundaries in frequency domain (Figure

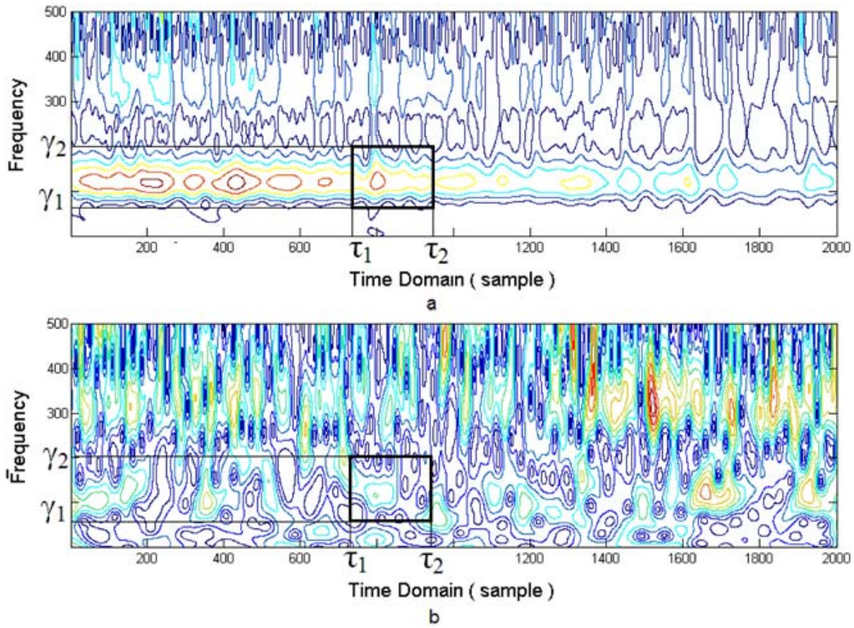

Figure 5.3: Local region boundaries in time-frequency domain: a) Vb = 0 and b) Vb = 0.50.

5.3). It is assumed that the time-frequency domain representation of the healthy signal and faulty signal are $S_h(t, f)$ and $S_f(t, f)$ respectively. It is proposed that for the rest of calculations, only the region of interest ($t \in [\tau_1, \tau_2]$ and $f \in [\gamma_1, \gamma_2]$) will be taken into account.

This research proposes an optimization based algorithm to find this region with the most discriminative information. Genetic algorithm is selected as the optimization method based on the nonlinear nature of the problem. The boundaries of the region of interest (τ_1, τ_2, γ_1, γ_2) should be find in a way that the region defined by them has most discriminative data and be suitable for fault detection problem (Figure5.3). The advantage of this method and its contribution is that both size and location of this region can be altered within the time-frequency domain until the best solution is found. A minimum and maximum limits are set for the length of this region as it should not cross the length of time-frequency output and be within

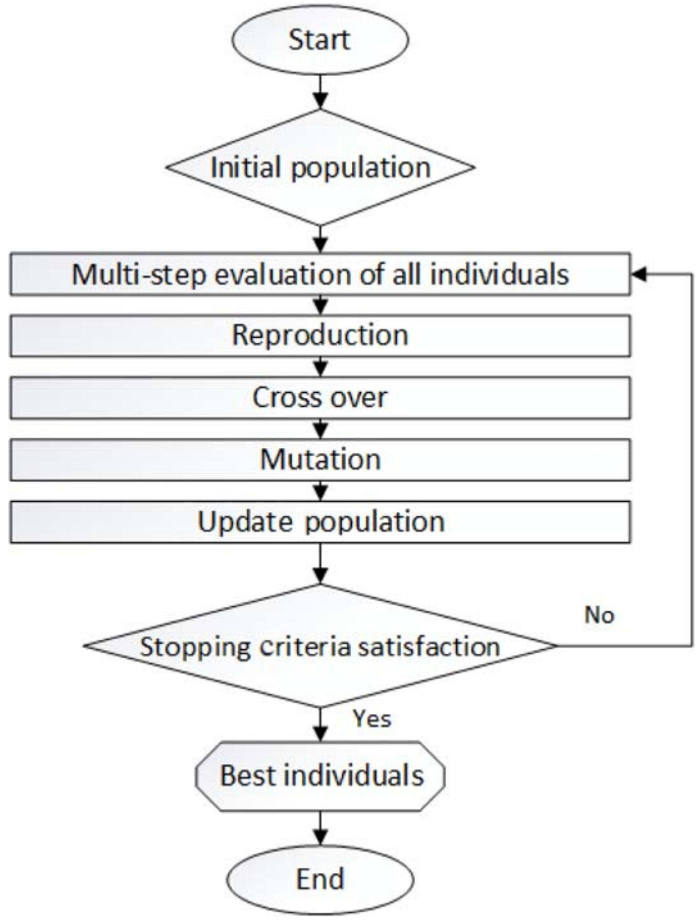

Figure 5.4: Flow chart of GA optimization method

an acceptable range.

The objective of optimization is to determine the coordinates of a region that can represent the signal relation with the fault characteristics and magnitude perfectly. For this purpose, signals of dataset are divided into three categories: training (65%), validation (15%) and test (20%). A multi-step nonlinear objective function is chosen to solve the problem. The same fault detection algorithm in previous chapter is also used in this section. The only difference is that instead of entire information of input signal, only the selected local region is fed to the system. In each iteration, a set of values will be selected for boundary conditions of the local region and a fault detection system is developed using training dataset.

Afterwards, the system accuracy is evaluated with the validation dataset and

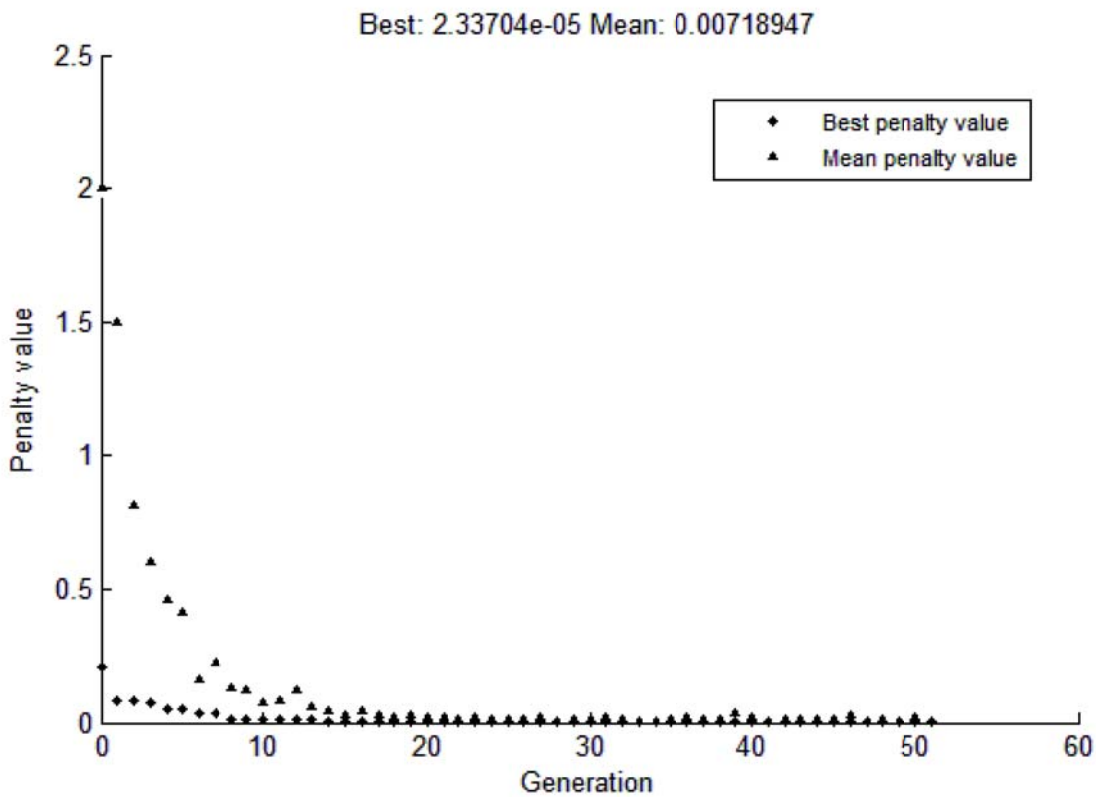

Figure 5.5: GA optimization trend

mean error is calculated exactly the same as former chapter. Making the mean error of the system minimum is the objective function of this problem. The boundaries of the local region are updated using the genetic algorithm rules and again the objective function is evaluated. After the GA procedure terminated and the local region boundaries are determined, the third subset of data which was unseen in the training and genetic algorithm steps is employed to evaluate and compare the result of the final system with the obtained boundaries from optimization problem. Figure 5.4depicts the steps of genetic algorithm procedure and Figure5.5shows its trend for one sample case.

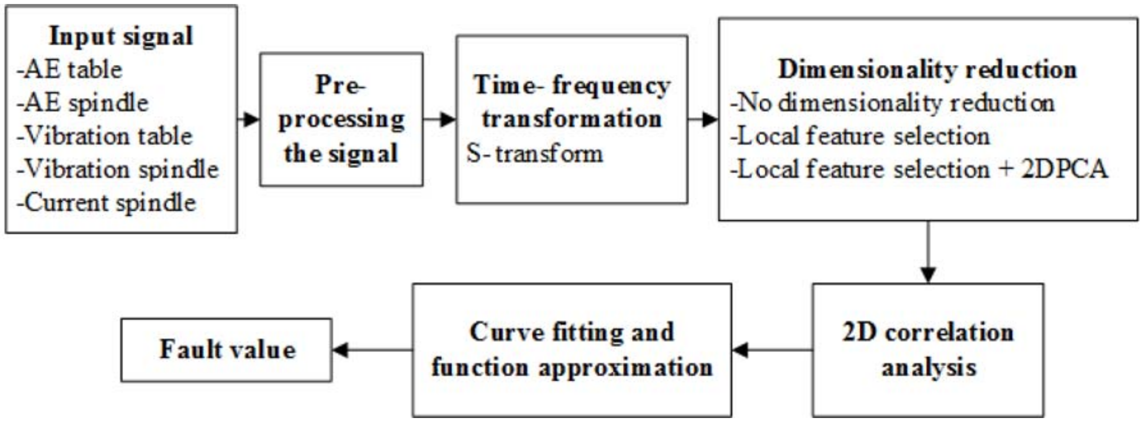

Figure 5.6: Monitoring systems' structure with different dimensionality reduction methods and various sets of input signals

5.3 Results and Analysis

The proposed method for dimensionality reduction is implemented and the results are compared with the result of the system without this method to evaluate its performance. Three scenarios have been investigated. The first scenario is using the entire time-frequency information output for correlation analysis and fault estimation. The second scenario is employing the proposed local feature generation to use an optimal region in time-frequency domain instead of entire information and the third one is to combine the proposed method with 2D PCA.

Figure 5.6 represents a schematic diagram of these cases. Five sets of input signals are employed to validate the work five times with different inputs. After the per-processing step and performing ST transformation, a dimensionality reduction strategy is conducted based on each explained scenarios. Finally 2D correlation analysis and curve fitting and function approximation approach determine a function between extracted features and fault values. The unseen test dataset is used for evaluation of accuracy of the systems and comparison.

Table5.1presents the mean error and maximum error of the monitoring systems in the explained three scenarios using different signals as input. While generally,

Table 5.1: Accuracy results of designed systems with different feature extraction and dimensionality reduction methods

Feature extraction methods	Time-frequency output		Local feature generation		Local feature generation + 2DPCA	
Input signals	Mean error %	Maximum error %	Mean error %	Maximum error %	Mean error %	Maximum error %
AE table	6.98	13.36	8.31	18.32	5.55	6.98
AE spindle	19.58	16.82	3.95	6.38	9.17	19.58
Vibration Table	25.86	34.12	14.56	28.44	10.44	25.86
Vibration spindle	21.54	36.17	4.03	35.86	4.09	21.54
AC current	6.19	14.27	5.85	11.59	3.16	6.19
Average	16.03	22.95	7.34	20.12	6.48	16.03

local feature generation of this work outperforms the conventional method and increases the accuracy and reliability significantly, combining it with 2D PCA can even lead to better results. Last row shows the average of errors in all the tested systems. The combination of proposed local feature generation and 2D PCA has the minimum average error of 6.48% while the local feature generation produces a system with the average error of 7.34% and conventional method average error is 12.10%.

The same trend is also evident in the maximum error. It is also important that the selected local area in time-frequency domain has less dimensions and therefore less calculation is needed in the correlation coefficients evaluation step that reduces the calculation cost significantly which is desirable for online applications. Figures 5.7and5.8represent the mean and maximum percentage error respectively for the systems.

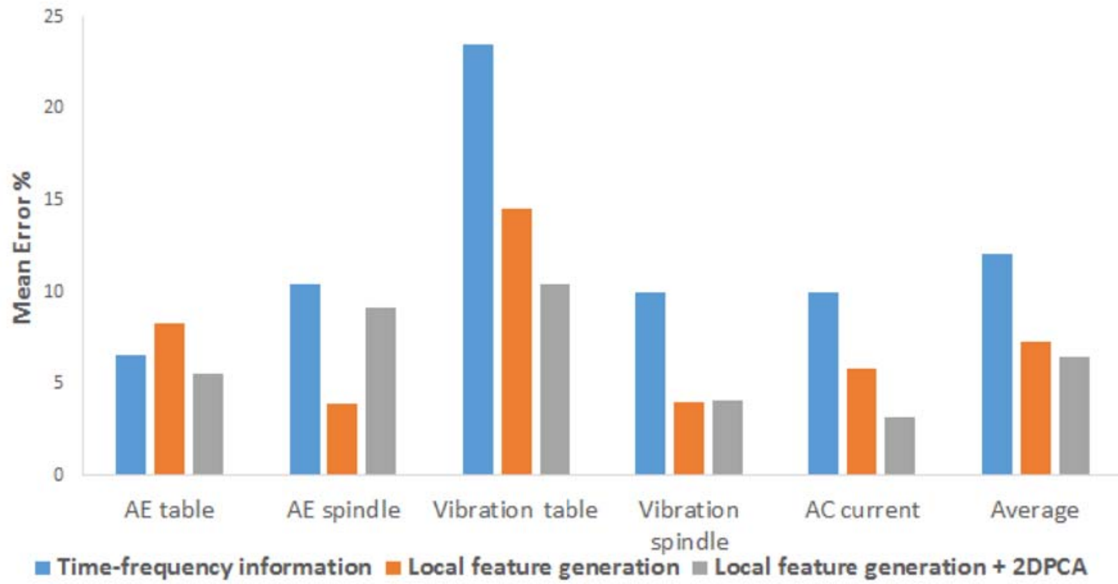

Figure 5.7: Mean percentage error of designed systems with different feature extraction and dimensionality reduction methods

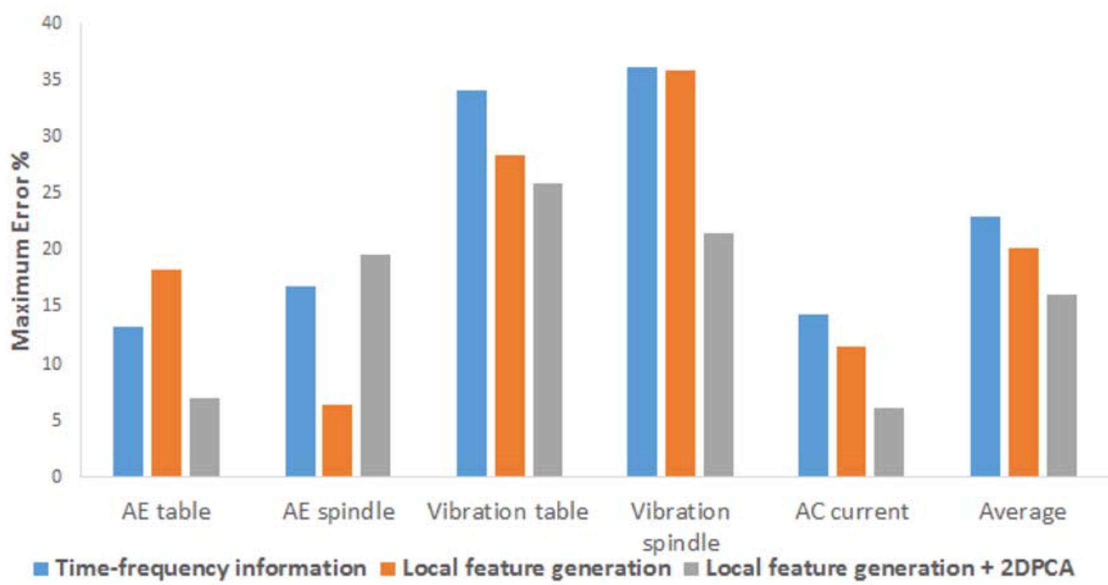

Figure 5.8: Maximum percentage error of designed systems with different feature extraction and dimensionality reduction methods

5.4 Chapter Summary

This chapter investigates a novel local time-frequency domain feature extraction method for tool condition monitoring in milling process. The output of time-frequency analysis has high dimensions and is costly for further investigations. This chapter proposed to use a local region of interest instead of entire information in time-frequency domain. An optimization approach is employed for finding the local region with the most discriminative information. Three cases are investigated and the results are compared. In the first case, the entire information of time-frequency output is implemented. In the second case, only a local region of interest determined by the proposed method is employed and in the third case, a combination of the local feature extraction method and 2D PCA is utilized. The results suggest that the combination of local feature extraction and 2D PCA provides best results and local feature extraction outperforms using the entire information.

Chapter 6

Fault Detection Using Artificial Intelligence Methods

6.1 Introduction

In the industrial machining process, environmental factors, machining parameters and fault characteristics are subjected to change. The use of indirect methods to predict faults also can provide additional unnecessary information. Moreover, the relation between fault variables and extracted features from signals is complex and has a non-linear nature. Therefore, an effective pattern recognition method is in demand with capability to learn complex non-linear relations. Artificial intelligence methods have shown great potential to perform such a task. In this chapter, three well-known and practical artificial intelligence methods are implemented to provide a model for fault diagnosis and estimation. Backgrounds of these methods are provided in the next section. Afterwards, a comparative study is conducted and the accuracy results for the algorithms are provided and discussed.

6.2 Background of Techniques

6.2.1 Multi-Layer Perceptron Artificial Neural Network (MLP-ANN)

Multi-layer perceptron is one the most widely used algorithms for pattern recognition in mechanical fault diagnosis. It is benefited from a feed-forward artificial neural network model consisting of an input layer, some hidden layers and an output layer. The procedure direction of feed-forward networks is from input layers to output layers and there is not any cycles or loops in the network. Each layer consists of some neurons which are connected to next layer with some connection weights. Knowledge in ANNs is stored as a set of connection weights. The process of modifying the connection weights is called training.

MLP utilizes backpropagation method for training the network. Let us assume W_{ab} represent the weights between the input and the hidden layers and W_{bc} represent the weights between the hidden and the output layers. The first iteration will be started by random weights . The operation of back error propagation (BEP) with a Tansig transfer function consists of following three stages[63]:

1- Feed-forward stage:

$$v(n) = w_{bc}(n)y(n); \tag{6.1}$$

$$o(n) = \varphi(v(n))) = \frac{2}{1+\exp[-2v(n)]}; \tag{6.2}$$

where n is the number of iterations, o is the output, y is the output of hidden layer and φ is the activation function. Based on this equation, the output of the network is derived for the current weights.

2- Back-propagation stage:

$$\delta(n) = e(n).\varphi[v(n)] = [d(n) - o(n)].[o(n)].[1 - o(n)]; \tag{6.3}$$

where δ represents the local gradient function, e shows the error function, o and d are the actual and desired outputs, respectively.

3- Adjust weighted value:

$$w_{ab}(n+1) = w_{ab}(n) + \Delta w_{ab}(n) = w_{ab}(n) + \eta\delta(n).o(n); \tag{6.4}$$

where η is the learning rate. Repeating these three stages conclude to a value of the error function that will be zero or a constant value.

6.2.2 Radial Basis Function Artificial Neural Network (RBF-ANN)

Radial basis function is another network structure introduced by Broomhead and Lowe[64]. This method employs radial basis functions as activation functions and the output of this network is a combination of radial basis functions of the inputs and neuron parameters. The output of the network ϕ is related to inputs X with the following function:

$$\varphi(X) = \sum_{i=1}^{N} a_i \rho(X - c_i) \tag{6.5}$$

where a_i is the weight of neuron i in the output layer, c_i is the center vector of neuron i and N is the number of neurons in the hidden layer. The method of this research uses a static Gaussian function as the nonlinearity for the hidden layer processing elements.

$$\rho\ (X - c_i) = \exp\ \left[-\beta\ X - {c_i}^2\right] \tag{6.6}$$

The important issue for successful implementation of this network is to find proper centers for the Gaussian functions as they responds only to a small region of the input space where the Gaussian is centered. A hybrid supervised-unsupervised topology is utilized for training of the system as supervised learning performs better to find suitable centers for the Gaussian functions, but an unsupervised approach usually produces better results.

6.2.3 Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive neuro-fuzzy inference system (ANFIS) integrates fuzzy systems and neural networks to capture the advantages of both. This method has the capability to generate and optimize fuzzy rule sets and parameters of membership function by training the fuzzy interference systems. The ANFIS employs a fuzzy Sugeno model in the framework of adaptive systems to facilitate learning and adaptation[65,66]. A single output Sugeno-type fuzzy interference system (FIS) is used to provide initial conditions for ANFIS training. Two membership functions, generalized Bell type and Gaussian-type, are employed based on the characteristics of each case. The generalized Bell type membership function can be defined with the following expression:

$$A_q^i(x) = \left(1 + \left|\frac{x - c_q^i}{a}\right|^{2b}\right)^{-1} \tag{6.7}$$

where c_q^i is the cluster center which defines the position of the membership function and a and b are parameters to define the shape of membership function. Gaussian-type membership function can be defined as follows:

$$A_q^i(x) \; = \exp\left[- 0.5\left(\frac{x - c_q^i}{\sigma_q^i}\right)^2\right] \tag{6.8}$$

where c_q^i is the center of cluster and σ_q^i is the dispersion of cluster. In a Sugeno fuzzy model utilized in this paper N fuzzy rules for a set of inputs are given by:

$$\begin{aligned}
&Rule\,1\ : If\ x_1\ is\ A_1^1,\ x_2\ is\ A_2^1,\ \ldots,\ x_q\ is\ A_q^1,\\
&then\ y^1\left(x_1,x_2,\ \ldots,\ x_q\right)=b_0^1+a_1^1x_1+a_2^1x_2+\ldots\ +\ a_q^1x_q\\
&\vdots\\
&Rule\,i\ : If\ x_1\ is\ A_1^i,\ x_2\ is\ A_2^i,\ \ldots,\ x_q\ is\ A_q^i,\\
&then\ y^i\left(x_1,x_2,\ \ldots,\ x_q\right)=b_0^i+a_1^ix_1n+a_2^ix_2+\ldots\ +\ a_q^ix_q\\
&\vdots\\
&Rule\,N\ : If\ x_1\ is\ A_1^N,\ x_2\ is\ A_2^N,\ \ldots,\ x_q\ is\ A_q^N,\\
&then\ y^N\left(x_1,x_2,\ \ldots,\ x_q\right)=b_0^N+a_1^Nx_1+a_2^Nx_2+\ldots\ +\ a_q^Nx_q
\end{aligned} \tag{6.9}$$

where $x_1,x_2,\ \ldots,\ x_q$ are the individual input variables and $y^i\ (\ i=1\ to\ N)$ are the first-order polynomial functions in the sequence. This method calculates the Sugeno-type FIS parameters using neural network. To train the system, a hybrid method of back-propagation and least-mean-square (LMS) is employed. Back-propagation method and LMS are utilized to determine the parameters associated with the input membership functions and to estimate the parameters associated with the output membership functions, respectively. The cost function to be minimized in the training problem has the following form:

$$\varepsilon=\frac{1}{2}(y_{des}-y\ )^2 \tag{6.10}$$

where y_{des} is the desired output. For each rule, the output $y^i(x_1,x_2,...,x_q)$ can be defined by:

$$y^i\left(t+1\right)=\ y^i\left(t\right)-k_y\frac{\partial\varepsilon}{\partial y^i} \tag{6.11}$$

where the k_y is the step size. The parameters for the jth membership function of the ith fuzzy rule for a generalized Bell-type membership function are determined as follows:

$$\begin{aligned} a_j^i(t+1) &= a_j^i(t) - k_c \frac{\partial \varepsilon}{\partial a_j^i} \\ b_j^i(t+1) &= b_j^i(t) - k_c \frac{\partial \varepsilon}{\partial b_j^i} \\ c_j^i(t+1) &= c_j^i(t) - k_c \frac{\partial \varepsilon}{\partial c_j^i} \end{aligned} \tag{6.12}$$

If a Gaussian-type membership function is used, the parameters of the jth membership function for the ith fuzzy rule are determined with the following equations:

$$\begin{aligned} \sigma_j^i(t+1) &= \sigma_j^i(t) - k_c \frac{\partial \varepsilon}{\partial \sigma_j^i} \\ c_j^i(t+1) &= c_j^i(t) - k_c \frac{\partial \varepsilon}{\partial c_j^i} \end{aligned} \tag{6.13}$$

Afterwards, the learning algorithm will tune all these modifiable parameters to make the ANFIS output match with the training data actual fault values.

6.3 Results of Comparison Between AI Methods

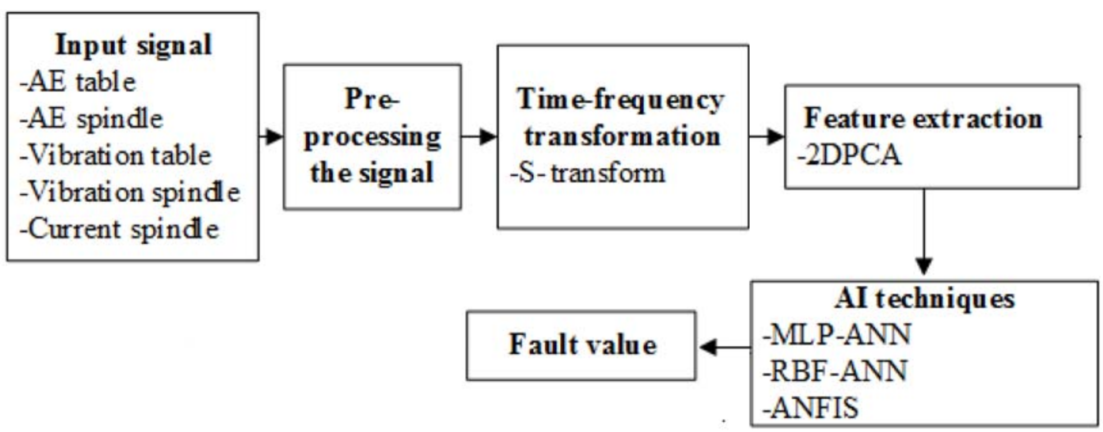

Figure 6.1: Monitoring systems structure with different AI methods and various sets of input signals

In this section, the effectiveness and performance of three well-known pattern recognition methods in the application of tool condition monitoring are investigated. Figure6.1represents the methodology and designing steps of systems in this chapter.

Table 6.1: Accuracy results of designed systems with different artificial intelligence methods

AI Methods	Adaptive Neuro Fuzzy Inference System (ANFIS)			Multi-Layer Perceptron Artificial Neural Network (MLP-ANN)			Radial Basis Function Artificial Neural Network (RBF-ANN)		
Input signals	Mean Err	Max Err	NRMSD	Mean Err	Max Err	NRMSD	Mean Err	Max Err	NMRSD
AE table	6.34	14.41	0.17	5.31	10.93	0.14	5.48	18.72	0.18
AE spindle	7.25	13.58	0.19	4.48	8.66	0.13	7.79	23.23	0.29
Vib table	8.84	15.93	0.25	10.31	27.9	0.33	8.53	28.87	0.3
Vib spindle	9.67	18.85	0.29	9.43	28.63	0.31	7.4	16.79	0.22
AC current	5.46	13.96	0.18	4.58	7.54	0.12	3.03	6.25	0.09
Average	7.51	15.35	0.22	6.82	16.73	0.21	6.45	18.77	0.22

All five dataset signals are used to compare the results of each AI technique based on the input signal of the system. For each system, 80% of the data is used for training step and 20% of the data is considered for test. The parameters of each system like number of neurons in each layer are optimized with genetic algorithm optimization method. To improve the training process, normalization is applied to all input data.

In each scenario, mean error of fault estimations for the test dataset, maximum error of fault estimations for the test dataset and normalized root mean square deviation (NRMSD) of the systems are reported to validate and compare the methods. NRMSD is the root mean square error divided by the range of the observed values of a variable being predicted. It can be calculated as follows:

$$NRMSD = \frac{\sqrt{\frac{\sum_{i=1}^{n}(y_e - y_o)}{n}}}{y_{max} - y_{min}} \tag{6.14}$$

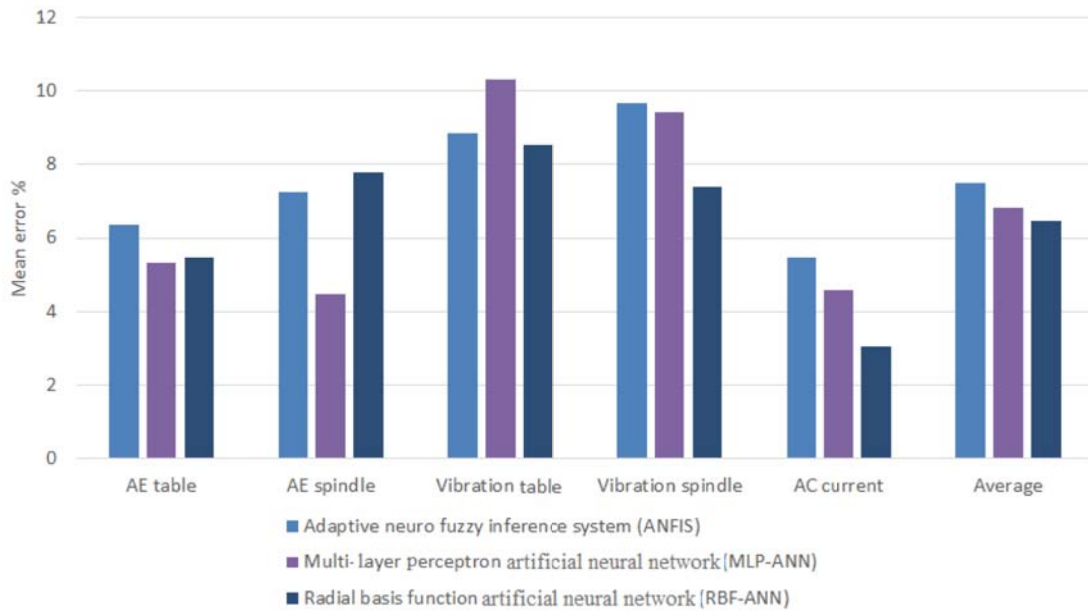

Figure 6.2: Fault estimation mean percentage error for different AI methods

where y_e denotes the estimated values of fault and y_o is observed value in the experiments.

The signals in the dataset contain cases with different operation conditions i.e. depth of cut and feed rate. The fault estimation results are presented in Table 6.1.

Figures 6.2 to 6.4 demonstrate the mean error, maximum error and NRMSD for the systems trained with different signals and pattern recognition methods respectively. It is observed that for systems with AE signal as input, MLP results outperforms RBF and ANFIS results. Superiority of MLP is noticeable in mean error, maximum error and NRMSD. The mean error of (4.48%) for the monitoring systems is achieved when AE sensor is mounted on the spindle of machining center and MLP is employed as the pattern recognition algorithm. The low maximum error of 8.66% also confirms the reliability of this system. NRMSD can be interpreted as a factor of stability of monitoring systems. NRMSD is also lower in AE based MLP systems which reflects higher stability of the monitoring algorithm in this case. While RBF gives more accurate results for the table AE signals as fault indicator in

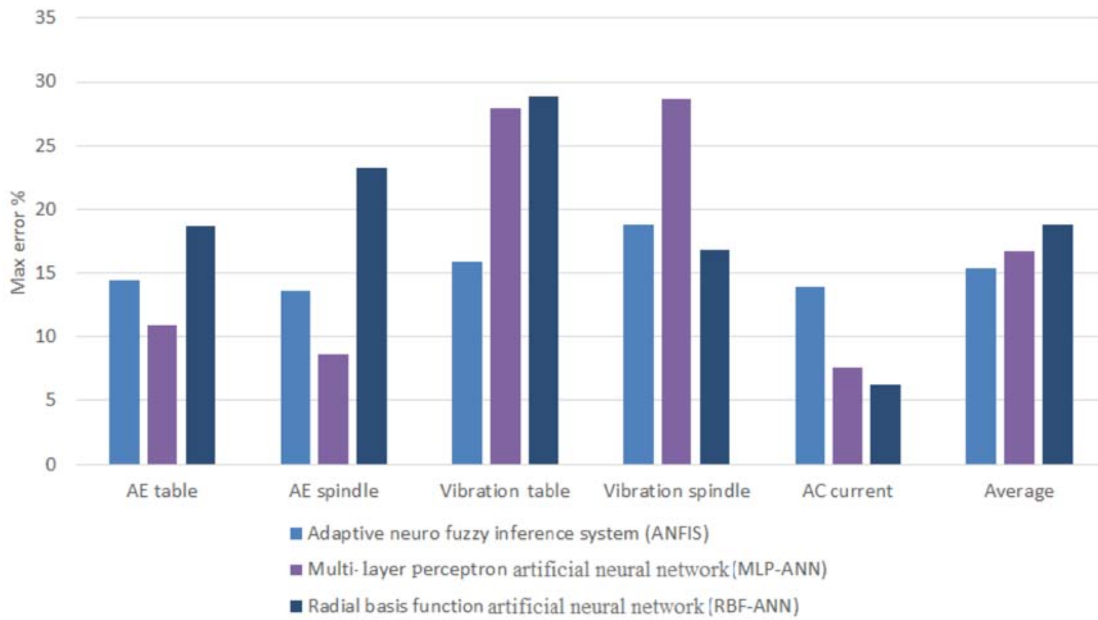

Figure 6.3: Fault estimation maximum percentage error for different AI methods

comparison to ANFIS, ANFIS surpass in AE spindle with lower maximum error.

When the vibration sensors are used as the fault indicator, RBF results outperform MLP and ANFIS by providing the minimum mean error. The most accurate system in this case is achieved by RBF when the sensor is mounted on the spindle with the 7.40% of fault estimation mean error. In this case, ANFIS provides low maximum error which makes it a reliable method as the maximum error does not exceeds 18.85% for any test samples.

For AC current also RBF provides the lowest mean error, maximum error and NRMSD. MLP is also superior to ANFIs in terms of accuracy, reliability and stability, when AC current signal is the input of the system.

The last row of the table shows the average errors for each column. It suggests that RBF has lowest average of mean errors in the systems and MLP also surpass the ANFIS method. However, in terms of maximum error, ANFIS has the lowest average. ANFIS errors in all the systems never exceed 18.85% while maximum error for MLP and RBF reaches to 28.63% and 28.87% respectively. It means that with an overall

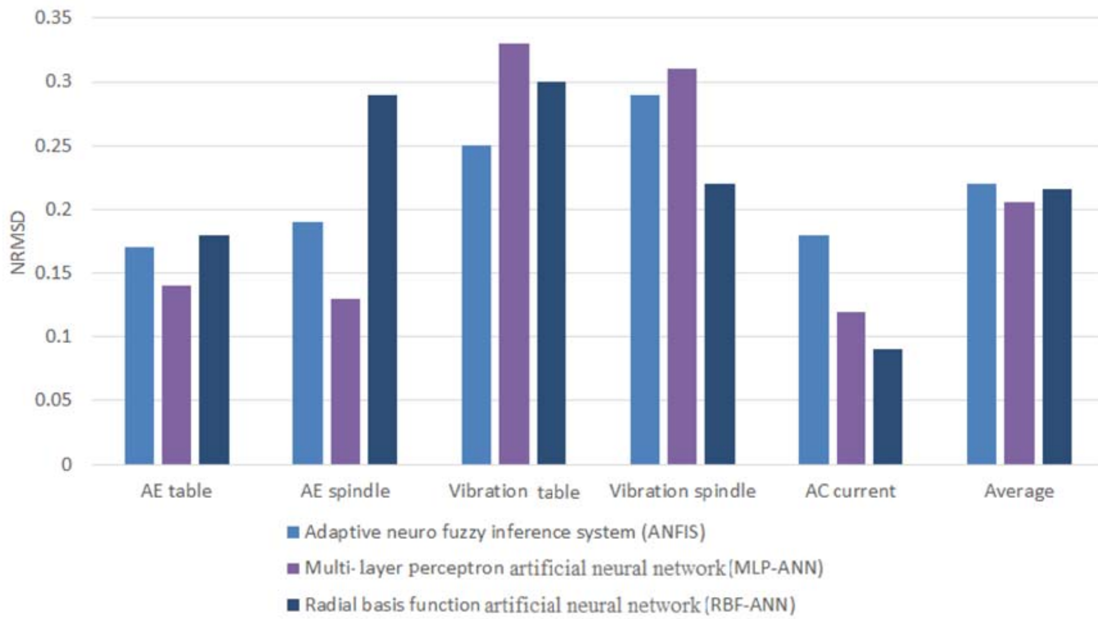

Figure 6.4: Fault estimation NRMSD for different AI methods

view, although ANFIS may not be as accurate as the other two pattern recognition methods in estimation of error, its error is always within acceptable limits. On the other hand, RBF and MLP provide accurate fault estimation results for the test dataset, however, their maximum error is generally higher than ANFIS.

6.4 Chapter Summary

This chapter studies the performance of different AI methods in the application of tool condition monitoring. After preparing proper features to describe the system fault, a pattern recognition algorithm is necessary to relate extracted features to system state. Multi-layer perceptron artificial neural network, radial basis function artificial neural network and adaptive neuro-fuzzy inference system are three tested algorithms in this chapter. All the dataset signals are utilized and the systems are designed with different inputs and the presented machine learning algorithms.

The results indicate that RBF-ANN provides the lowest mean error while MLP-ANN outperforms ANFIS. In contrast, ANFIS provides lowest maximum error which implies that the error is within an acceptable limit.

Chapter 7

Conclusion and Future Works

7.1 Conclusion

This research investigates the design of automated, reliable tool condition monitoring systems in machining process using time-frequency transformation and AI methods. Flank wear in particular is explored as one of the most common tool faults in machining process. The methodology is explained in Chapter2. Designing an AI based machining monitoring system comprised of four main steps: 1) signal acquisition, 2) signal processing, 3) feature extraction/selection and 4) decision making using AI methods. Each chapter from Chapter3to6is investigated on one of these steps.

Chapter3investigates using multiple sensors to improve the accuracy and robustness of monitoring algorithm. It examines many pairs of signals in multi-sensor systems as well as sensor fusion and compares the results with the single signal systems. Afterwards, it investigates the strategies of data fusion and compares three methodology for data combination: 1) feature level, 2) score level, and 3) decision level.

The highest accuracy was achieved when the AE of spindle and AC current signals are used with score level sensor fusion. AC current signal is a perfect candidate as a complementary information for other signals based on its low cost, simultaneously, it can improve the accuracy significantly. However, using it individually may not satisfy the reliability conditions. In contrast, AE and vibration signals can be used individually with acceptable results. AE signal is also a suitable candidate with high potential for sensor fusion with vibration and AC current as its nature is less correlated to them.

Results show that in using two different types of sensors, it is better to place them in different locations rather than placing both of them at the same place. Furthermore, while well selected sensor fusion signals can improve the monitoring system accuracy significantly, using multiple sensors from the same type do not have a significant effect on the system. It can be helpful to improve the reliability in the case that if one of the sensors fails the other performs the task.

A comparison between different levels of data fusion reveals that score level data fusion is superior to two other methods while decision level data fusion gives better results than feature level.

Chapter4studies three linear time-frequency transformation methods in condition monitoring application, STFT, WT and ST, and two bilinear time-frequency distribution, smoothed Pseudo-Wigner–Ville and Choi–Williams for signal processing step and the results of different systems designed with each method are extracted and compared.

It is shown that ST outperforms other methods and provides the monitoring systems with less average error and higher accuracy. Wavelet transform also as a widely used technique for condition monitoring shows promising results. Maximum error is also reported for each case as a representative of the systems reliability. The results show that ST and WT also produce the monitoring systems with comparatively low maximum errors. The other three time-frequency transformation methods also provide acceptable results which suggest time-frequency transformation as a powerful tool to design solid monitoring systems.

Chapter5explores feature generation, extraction/selection techniques. A novel feature extraction method is proposed and tested in this chapter. This method was based on using information of a local region in time-frequency domain with most discriminative information rather than using the entire data. This region is obtained by GA optimization.

The results from the experiments show that the proposed method can improve the accuracy and reliability of the monitoring system significantly. This method not only improves the accuracy, but also is able to decrease the calculation cost by reducing the dimensionality of the data and facilitate the online tool condition monitoring procedure. A hybrid algorithm based on the proposed local feature generation method and 2D PCA is also presented which provided the most accurate result in comparison to other cases.

Chapter5investigates AI methods for the last step of monitoring algorithm. Three well-known AI methods, ANFIS, MLP-ANN and RBF-ANN are employed to build a model between the extracted features and fault values.

The results show that RBF provides more accurate results for tool condition monitoring in overall. MLP also outperforms ANFIS considering the average of mean errors in all the systems. However, all the methods can be considered to provide promising results. It is also concluded that although ANFIS results were not as accurate as two other methods in terms of mean error, its error range is lower than two other methods and the maximum error never exceeds 19% in any cases which makes it superior with respect to reliability.

Finally, this research proposes a monitoring system with 1) AE of spindle and AC current as input signals, 2) S-transform as the time-frequency analysis method, 3) the hybrid method of local feature extraction and 2D PCA for dimensionality reduction and feature generation, and 4) RBF as the decision-making model to achieve an accurate monitoring system for this dataset.

The main contributions of this work can be summarized as:

- This research investigated multi-sensor systems and compares using multiple sensors from the same type, sensor fusion and using a single signal. It also examines the effects of sensors' location on the monitoring systems.
- It proposed recommendations on which pairs of signals provide more comprehensive and complimentary information based on the research results.
- It investigated different strategies of data fusion and their performance in tool condition monitoring.
- It perform a comparative study on five of the most common time-frequency transformation methods and their application in tool condition monitoring.
- It proposed a novel dimensionality reduction method which improves the monitoring accuracy by providing the most discriminative local region in time-frequency domain and reducing the calculation cost significantly which is necessary for online application
- This research employs a combination of the proposed dimensionality reduction method with 2D PCA which produces monitoring systems with even more accurate results.
- This research conducts a comparative study between three of the most commonly used machine learning methodologies in tool condition monitoring and investigates their advantages and disadvantages.
- It uses a real benchmark milling data for validation which makes it more credible for industrial use.

- Finally, this research develops an accurate, automatic, tool condition monitoring algorithm which uses practical sensors and is capable to work online and under changing operation conditions.

7.2 Publications

The following research papers are published/submitted based on the results of this research:

Published:

- Javad Soltani Rad, Fatemeh Aghazadeh, Youmin Zhang, Chevy Chen, A study on tool wear monitoring using time-frequency transformation techniques, Presented in *International Conference on Innovative Design and Manufacturing (ICIDM)*, Montreal, Canada, 2014

- Javad Soltani Rad, Youmin Zhang, Chevy Chen, A novel local time-frequency domain feature extraction method for tool condition monitoring using s-transform and genetic algorithm, Presented in *The 19th World Congress of the International Federation of Automatic Control (IFAC 2014)*, Cape Town, South Africa, 2014

- Javad Soltani Rad, Ensieh Hosseini, Youmin Zhang, Chevy Chen, Online tool wear monitoring and estimation using power signals and S-transform, presented in *2nd International Conference on Control and Fault-Tolerant Systems* (SysTol2013), Nice, France, 2013

Under review:

- Javad Soltani Rad, Fatemeh Aghazadeh, Youmin Zhang, Chevy Chen, A comprehensive study on tool condition monitoring using time-frequency transformation and artificial intelligence, Submitted to *Mechanical Systems and Signal*

Processing, ISSN: 0888-3270

- Javad Soltani Rad, Fatemeh Aghazadeh, Youmin Zhang, Chevy Chen, A sensor fusion based tool condition monitoring for milling operation using S-Transform technique, *Submitted to The International Journal of Advanced Manufacturing Technology*, ISSN: 0268-3768

7.3 Future Works

There is a high potential and need for researches in different directions of manufacturing fields as growing demand of industries on manufacturing processes. This research has investigated designing an online tool condition monitoring technique to maximize the usage period of a tool, predict tool wear, prevent tool breakage and stop the process before machine or workpiece being damaged or destroyed. Moreover, it provides tool wear information for possible process optimization and tool compensation. This research can be improved in the following directions:

- In signal acquisition step, more sensors such as temperature sensors, ultrasonic sensors, etc. can be mounted to the system at different positions and their performance can be evaluated.

- The experiments can be repeated for different machines and with more operation conditions and effects of changing these factors can be investigated on the monitoring systems.

- In signal processing step, more advanced techniques and modern signal processing methods can be evaluated for this application.

- A modified version of signal processing algorithms may be adjusted to online application with lower computational cost. For instance, fast S-transform is a modified version of ST which can be applied in this problem.

- Dimensionality reduction as one of the most important steps always needs to be improved as it provides the features of the signal for fault detection. More studies and researches should be conducted in this area to find features which are less dependent on the cutting parameters and more informative with respect to monitoring variable. For instance, finding an approach for normalizing the features to operation conditions is a subject with high potential to be investigated.

- In the case of using PCA or similar methods for dimensionality reduction, an optimization method can select a final set of features from the ranked output of PCA.

- Based on the extracted features and knowledge of the process, more advanced and modern AI methods can be implemented and tested in decision making unit.

- Ensemble of classifiers can be utilized for more accurate and reliable results. It should be determined that which methods can be used together and also different ensembles strategies should be implemented and compared in this application.

- Methodologies for online optimization of cutting parameters based on the reported fault values by the monitoring system may be designed.

- A reliability analysis of the monitoring systems under different cutting parameters than they were trained for is beneficial to design more robust and general methods.

- One of the issues of these monitoring systems is that they can not easily be implemented on other machines than the one they were trained for. An study to provide solutions for adjusting one monitoring algorithm designed for one machine to another machines with minimum number of experiments and cost has to be investigated.

- This research investigates fault diagnosis and estimation. More researches should focus on prognosis to determine the fault growth and tool life. This study requires precise experiment design and research on fault growth over time.

- This study investigates tool flank wear as the monitoring variable. Other common machining faults can be also investigated. Time-frequency analysis can be helpful for this purpose due to its ability to provide vast information of the signals. A unique signature for each specific fault may be discovered in time-frequency domain to help detect a specific fault in the systems with multiple-faults.

Bibliography

[1]A. G. Rehorn, J. Jiang, and P. E. Orban, “State-of-the-art methods and results in tool condition monitoring: a review,” *The International Journal of Advanced Manufacturing Technology*, vol. 26, no. 7-8, pp. 693–710, 2005.

[2]R. Todd, D. Allen, and L. Alting, *Manufacturing Processes Reference Guide*. Industrial Press, 1994.

[3]A. G. Rehorn, E. Sejdic, and J. Jiang, “Fault diagnosis in machine tools using selective regional correlation,” *Mechanical Systems and Signal Processing*, vol. 20, no. 5, pp. 1221–1238, 2006.

[4]J. Usher, *The Modern Machinist: A Practical Treatise on Modern Machine Shop Methods*. N. W. Henley, 1896.

[5]M. Groover, *Fundamentals of Modern Manufacturing: Materials, Processes, and Systems*. John Wiley & Sons, 2010.

[6]M. A. Elbestawi, M. Dumitrescu, and E.-G. Ng, *Tool condition monitoring in machining*, pp. 55–82. Condition Monitoring and Control for Intelligent Manufacturing, Springer, 2006.

[7]N. Ghosh, Y. B. Ravi, A. Patra, S. Mukhopadhyay, S. Paul, A. R. Mohanty, and A. B. Chattopadhyay, “Estimation of tool wear during CNC milling using

neural network-based sensor fusion," *Mechanical Systems and Signal Processing*, vol. 21, pp. 466–479, 1 2007.

[8] F. Camci and R. B. Chinnam, "Process monitoring, diagnostics and prognostics in machining processes," *LAP Lambert Academic Publishing, Germany*, p. 978, 2010.

[9] "Wikipedia, http://en.wikipedia.org/wiki/turning, accessed on 03-18-15,"

[10] K. Danai, "Machine tool monitoring and control, chapter 5 of mechanical systems design handbook: Modeling," *Measurement, and Control. CRC Press*, pp. 75–84, 2001.

[11] "http://www.sandvik.coromant.com/sitecollectionimages/technical-guide accessed on 03-18-15,"

[12] "http://www.drillingknowledge.com/wp-content/uploads/25-12.jpg, accessed on 03-18-15,"

[13] J. Abellan-Nebot and F. R. Subion, "A review of machining monitoring systems based on artificial intelligence process models," *The International Journal of Advanced Manufacturing Technology*, vol. 47, pp. 237–257, 2010/03/01 2010.

[14] A. Siddhpura and R. Paurobally, "A review of flank wear prediction methods for tool condition monitoring in a turning process," *The International Journal of Advanced Manufacturing Technology*, vol. 65, no. 1-4, pp. 371–393, 2013.

[15] J. Zhang and J. Chen, "Tool condition monitoring in an end-milling operation based on the vibration signal collected through a microcontroller-based data acquisition system," *The International Journal of Advanced Manufacturing Technology*, vol. 39, no. 1-2, pp. 118–128, 2008.

[16]A. G. Rehorn, J. Jiang, and P. E. Orban, "State-of-the-art methods and results in tool condition monitoring: a review," *The International Journal of Advanced Manufacturing Technology*, vol. 26, pp. 693–710, 2005/10/01 2005.

[17]B. H. Freyer, P. S. Heyns, and N. J. Theron, "Comparing orthogonal force and unidirectional strain component processing for tool condition monitoring," *Journal of Intelligent Manufacturing*, vol. 25, no. 3, pp. 473–487, 2014.

[18]S. Zhang, J. Li, and Y. Wang, "Tool life and cutting forces in end milling inconel 718 under dry and minimum quantity cooling lubrication cutting conditions," *Journal of Cleaner Production*, vol. 32, pp. 81–87, 2012.

[19]G. Wang, Y. Yang, and Z. Guo, "Hybrid learning based gaussian artmap network for tool condition monitoring using selected force harmonic features," *Sensors and Actuators A: Physical*, vol. 203, pp. 394–404, 2013.

[20]G. Wang, Z. Guo, and Y. Yang, "Force sensor based online tool wear monitoring using distributed gaussian artmap network," *Sensors and Actuators A: Physical*, vol. 192, no. 0, pp. 111–118, 2013.

[21]X. Chen and H. Li, "Development of a tool wear observer model for online tool condition monitoring and control in machining nickel-based alloys," *The International Journal of Advanced Manufacturing Technology*, vol. 45, no. 7-8, pp. 786–800, 2009.

[22]K. Zhu, Y. S. Wong, and G. S. Hong, "Multi-category micro-milling tool wear monitoring with continuous hidden markov models," *Mechanical Systems and Signal Processing*, vol. 23, no. 2, pp. 547–560, 2009.

[23]T.-I. Liu, S.-D. Song, G. Liu, and Z. Wu, "Online monitoring and measurements of tool wear for precision turning of stainless steel parts," *The International*

Journal of Advanced Manufacturing Technology, vol. 65, no. 9-12, pp. 1397–1407, 2013.

[24] H. Rafezi, J. Akbari, and M. Behzad, "Tool condition monitoring based on sound and vibration analysis and wavelet packet decomposition," in *Mechatronics and its Applications (ISMA), 2012 8th International Symposium on*, pp. 1–4, IEEE, 2012.

[25] M. Bhuiyan, S. Choudhury, and Y. Nukman, "Tool condition monitoring using acoustic emission and vibration signature in turning," in *Proceedings of the world congress on engineering*, vol. 3, 2012.

[26] G. Wang, Y. Yang, Y. Zhang, and Q. Xie, "Vibration sensor based tool condition monitoring using ν support vector machine and locality preserving projection," *Sensors and Actuators A: Physical*, vol. 209, pp. 24–32, 2014.

[27] M. Prakash, P. Ravisankar, and M. Kanthababu, "Acoustic emission signal analysis for tool condition monitoring in microendmilling of aluminium alloy," in *Advanced Materials Research*, vol. 984, pp. 25–30, Trans Tech Publ, 2014.

[28] S. Pai, T. Nagabhushana, and R. B. Rao, "Tool condition monitoring using acoustic emission, surface roughness and growing cell structures neural network," *Machining Science and Technology*, vol. 16, no. 4, pp. 653–676, 2012.

[29] H. Chelladurai, V. Jain, and N. Vyas, "Development of a cutting tool condition monitoring system for high speed turning operation by vibration and strain analysis," *The International Journal of Advanced Manufacturing Technology*, vol. 37, no. 5-6, pp. 471–485, 2008.

[30] C.-L. Yen, M.-C. Lu, and J.-L. Chen, "Applying the self-organization feature map (som) algorithm to ae-based tool wear monitoring in micro-cutting," *Mechanical Systems and Signal Processing*, vol. 34, pp. 353–366, 1 2013.

[31] I. Marinescu and D. A. Axinte, “A critical analysis of effectiveness of acoustic emission signals to detect tool and workpiece malfunctions in milling operations,” *International Journal of Machine Tools and Manufacture*, vol. 48, no. 10, pp. 1148–1160, 2008.

[32] W. Xiao, Y. Zi, B. Chen, B. Li, and Z. He, “A novel approach to machining condition monitoring of deep hole boring,” *International Journal of Machine Tools and Manufacture*, vol. 77, pp. 27–33, 2 2014.

[33] S. Kosaraju, V. Anne, and B. Popuri, “Online tool condition monitoring in turning titanium (grade 5) using acoustic emission: modeling,” *The International Journal of Advanced Manufacturing Technology*, vol. 67, no. 5-8, pp. 1947–1954, 2013.

[34] A. Ammouri and R. Hamade, “Current rise criterion: a process-independent method for tool-condition monitoring and prognostics,” *The International Journal of Advanced Manufacturing Technology*, vol. 72, no. 1-4, pp. 509–519, 2014.

[35] T. I. Ogedengbe, R. Heinemann, and S. Hinduja, “Feasibility of tool condition monitoring on micro-milling using current signals,” *AU Journal of Technology*, vol. 14, pp. 161–172, 2011.

[36] J. S. Rad, E. Hosseini, Y. Zhang, and C. Chen, “Online tool wear monitoring and estimation using power signals and s-transform,” in *Control and Fault-Tolerant Systems (SysTol)*, pp. 234–238, 2013.

[37] C. Aliustaoglu, H. M. Ertunc, and H. Ocak, “Tool wear condition monitoring using a sensor fusion model based on fuzzy inference system,” *Mechanical Systems and Signal Processing*, vol. 23, pp. 539–546, 2 2009.

[38] W. Wang, G. Hong, Y. Wong, and K. Zhu, “Sensor fusion for online tool condition monitoring in milling,” *International Journal of Production Research*, vol. 45, no. 21, pp. 5095–5116, 2007.

[39] S. Cho, S. Binsaeid, and S. Asfour, “Design of multisensor fusion-based tool condition monitoring system in end milling,” *The International Journal of Advanced Manufacturing Technology*, vol. 46, no. 5-8, pp. 681–694, 2010.

[40] F. Al-Badour, M. Sunar, and L. Cheded, “Vibration analysis of rotating machinery using time–frequency analysis and wavelet techniques,” *Mechanical Systems and Signal Processing*, vol. 25, no. 6, pp. 2083–2101, 2011.

[41] Z. Feng, M. Liang, and F. Chu, “Recent advances in time-frequency analysis methods for machinery fault diagnosis: A review with application examples,” *Mechanical Systems and Signal Processing*, vol. 38, no. 1, pp. 165–205, 2013.

[42] L. D. Avendano-Valencia, C. D. Acosta-Medina, and G. Castellanos-Dominguez, *Time-Frequency Based Feature Extraction for Non-Stationary Signal Classification*, p. 13. Applied Biomedical Engineering, InTech, 2011.

[43] D. Dimla, P. Lister, and N. Leighton, “Neural network solutions to the tool condition monitoring problem in metal cutting—a critical review of methods,” *International Journal of Machine Tools and Manufacture*, vol. 37, no. 9, pp. 1219–1241, 1997.

[44] T.-I. Liu and B. Jolley, “Tool condition monitoring (tcm) using neural networks,” *The International Journal of Advanced Manufacturing Technology*, pp. 1–9, 2015.

[45] K. V. Rao, B. Murthy, and N. M. Rao, “Prediction of cutting tool wear, surface roughness and vibration of work piece in boring of aisi 316 steel with artificial neural network,” *Measurement*, vol. 51, pp. 63–70, 2014.

[46]V. Kalaichelvi, R. Karthikeyan, D. Sivakumar, and V. Srinivasan, "Tool wear classification using fuzzy logic for machining of al-sic composite material," *Modeling and Numerical Simulation of Material Science*, vol. 2, no. 02, p. 28, 2012.

[47]Q. Ren, R. Botez, P. Bigras, M. Balazinski, and L. Baron, "Tool wear assessment based on type-2 fuzzy uncertainty estimation on acoustic emission," *Applied Soft Computing*, 2015.

[48]A. Gajate, R. Haber, R. del Toro, P. Vega, and A. Bustillo, "Tool wear monitoring using neuro-fuzzy techniques: a comparative study in a turning process," *Journal of Intelligent Manufacturing*, vol. 23, no. 3, pp. 869–882, 2012.

[49]S. S. Gill, R. Singh, J. Singh, and H. Singh, "Adaptive neuro-fuzzy inference system modeling of cryogenically treated aisi m2 hss turning tool for estimation of flank wear," *Expert Systems with Applications*, vol. 39, no. 4, pp. 4171–4180, 2012.

[50]M. Rizal, J. A. Ghani, M. Z. Nuawi, and C. H. C. Haron, "Online tool wear prediction system in the turning process using an adaptive neuro-fuzzy inference system," *Applied Soft Computing*, vol. 13, no. 4, pp. 1960–1968, 2013.

[51]D. Tobon-Mejia, K. Medjaher, and N. Zerhouni, "CNC machine tool's wear diagnostic and prognostic by using dynamic bayesian networks," *Mechanical Systems and Signal Processing*, vol. 28, pp. 167–182, 2012.

[52]T. Boutros and M. Liang, "Detection and diagnosis of bearing and cutting tool faults using hidden markov models," *Mechanical Systems and Signal Processing*, vol. 25, no. 6, pp. 2102–2124, 2011.

[53]B. Kaya, C. Oysu, H. M. Ertunc, and H. Ocak, "A support vector machine-based online tool condition monitoring for milling using sensor fusion and a

genetic algorithm," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 226, no. 11, pp. 1808–1818, 2012.

[54] A. Agogino and K. Goebel, "Mill data set," *BEST lab, UC Berkeley. NASA Ames Prognostics Data Repository, [http://ti. arc. nasa. gov/project/prognostic-data-repository], NASA Ames, Moffett Field, CA*, 2007.

[55] J. Yang, D. Zhang, A. F. Frangi, and J.-Y. Yang, "Two-dimensional pca: a new approach to appearance-based face representation and recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 26, no. 1, pp. 131–137, 2004.

[56] W.-M. Zuo, K.-Q. Wang, and D. Zhang, "Assembled matrix distance metric for 2dpca-based face and palmprint recognition," in *Machine Learning and Cybernetics, 2005*, vol. 8, pp. 4870–4875, 2005.

[57] J. Allen and L. Rabiner, "A unified approach to short-time fourier analysis and synthesis," *Proceedings of the IEEE*, vol. 65, pp. 1558–1564, Nov 1977.

[58] R. G. Stockwell, L. Mansinha, and R. P. Lowe, "Localization of the complex spectrum: the s transform," *IEEE Transactions on Signal Processing*, vol. 44, no. 4, pp. 998–1001, 1996.

[59] I. Djurovic, E. Sejdic, and J. Jiang, "Frequency-based window width optimization for s-transform," *AEU - International Journal of Electronics and Communications*, vol. 62, no. 4, pp. 245–250, 2008.

[60] R. G. Stockwell, "A basis for efficient representation of the s-transform," *Digital Signal Processing*, vol. 17, pp. 371–393, 1 2007.

[61] T. Claasen and W. Mecklenbrauker, "The wigner distribution—a tool for time-frequency signal analysis. part ii: Discrete-time signals," *Philips J. Res*, vol. 35, no. 3, pp. 276–300, 1980.

[62] H.-I. Choi and W. J. Williams, "Improved time-frequency representation of multicomponent signals using exponential kernels," *IEEE Transactions on Acoustics, Speech and Signal Processing*, vol. 37, no. 6, pp. 862–871, 1989.

[63] J. L. McClelland, D. E. Rumelhart, P. R. Group, *et al.*, "Parallel distributed processing," *Explorations in the Microstructure of Cognition*, vol. 2, pp. 216–271, 1986.

[64] D. S. Broomhead and D. Lowe, "Radial basis functions, multi-variable functional interpolation and adaptive networks," *Tec. Rep., DTIC Document, 1988.*

[65] J.-S. Jang, "Anfis: adaptive-network-based fuzzy inference system," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 23, no. 3, pp. 665–685, 1993.

[66] T. Grigorie and R. Botez, "Adaptive neuro-fuzzy inference system-based controllers for smart material actuator modelling," *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering*, vol. 223, no. 6, pp. 655–668, 2009.